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

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

17   **Abstract**
18   The gains from digital technology diffusion are deemed essential for international development, but

19   they are also distributed unevenly. Does the uneven distribution mean that not everyone benefits from

20   new technologies to the same extent, or do some people experience an absolute disadvantage during

21   this process? I explore this question through the case study of healthcare access in the context of rapid

22   mobile phone uptake in rural India, contributing thus to an important yet surprisingly under-researched

23   aspect of the social implications of (mobile) technology diffusion.

24   Inspired by a previous analysis of cross-sectional data from rural India, I hypothesise that health

25   systems increasingly adapt to mobile phone users where phones have diffused widely. This adaptation

26   will leave poor non-adopters worse off than before and increases healthcare inequities. I use a panel

27   of 12,003 rural households with an illness in 2005 and 2012 from the Indian Human Development

28   Survey to test this hypothesis. Based on village-cluster robust fixed-effects linear probability models,

29   I find that (a) mobile phone diffusion is significantly and negatively linked to various forms of rural

30   healthcare access, suggesting that health systems increasingly adapt to phone use and discriminate

31   against non-users; that (b) poor rural households without mobile phones experience more adverse

32   effects compared to more affluent households, which indicates a struggle and competition for

33   healthcare access among marginalised groups; and that (c) no effects emerge for access to public

34   doctors, which implies that some healthcare providers are less responsive to mobile phone use than

35   others.

36   Overall, my findings indicate that the rural Indian healthcare system gradually adapts to increasing

37   mobile phone use at the expense of non-users. I conclude that rapid mobile phone diffusion creates an

38   opportunity to improve people's access to healthcare in rural India, but it also creates new forms of

39   marginalisation among poor rural households.

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43   **Highlights**

44   • This study relates to the social implications of technology diffusion

45   • I hypothesise that mobile phone diffusion undermines healthcare access for non-adopters

46   • I use a panel of 12,003 sick households across rural India in 2005 and 2012

47   • Poor households have worse access to private care if they fail to adopt during fast diffusion

48   • Wealthier households and public healthcare access are insulated from this trend

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55 **1   Introduction**

56   It is a common stance that the diffusion of information and communication technology (ICT)

57 is essential for development (Aker & Mbiti, 2010:229; Donner, 2015:14; Heeks, 2008:26), but what if

58 the process of digital inclusion is a struggle that leaves excluded groups *worse off* than before? I

59 investigate this question through the case study of phone-aided healthcare access in rural India between

60 2005 and 2012, demonstrating that the increased availability of mobile phones intensifies competition

61 for scarce healthcare services among poor rural households. While poor phone owners enjoy more

62 access to private doctors in contexts of rapid mobile phone diffusion, the slow-growing supply of

63 healthcare and a system that caters increasingly to phone users mean that poor households without

64 mobile phones see their access to healthcare diminish. Left to their own devices, mobile phone adopters

65 thus outcompete non-adopters in the struggle for scarce rural healthcare services.[1] All the while, more

66 affluent households with a broader range of options to access healthcare are insulated from these

67 developments.

68   This research was motivated by the literature on "information and communication technologies

69 and development" (ICTD), which has begun to examine the inequalities of technology adoption

70 (Donner, 2015:137-154; Graham *et al.*, 2014:758-759; Napoli & Obar, 2014; Schroeder, 2015:2828-

71 2830; van Dijk, 2005:22), but which tends to assume that diffusion itself is desirable and that nobody

72 experiences an absolute disadvantage through it. Contrary to this position, an earlier mixed-methods

73 research project on healthcare-related mobile phone use in rural India and rural China suggested that

74 widespread mobile phone use can lead to an adverse over-utilisation of resource-constrained rural

75 healthcare systems, which can leave digitally excluded groups at a growing disadvantage (Haenssgen,

76 2015a, 2015b, 2015c). Because the cross-sectional study was not designed to capture long-term and

77 systemic effects of mobile phone diffusion, the present paper uses India-wide panel data from the

78 Indian Human Development Survey (IHDS; Desai *et al.*, 2010b; Desai *et al.*, 2016). Adopting a

79   process perspective of mobile-phone-aided healthcare access, I hypothesise that the increasing spread

80   of mobile phones in rural India worsens healthcare access for digitally excluded households.

81   This paper contributes to the interdisciplinary study of the social implications of technology

82   diffusion in general, and to the study of digital divides in the field of ICTD in particular. It advances

83   the conceptualisation of digital inclusion through an empirically grounded process framework of

84   technology adoption that appreciates dynamic and systemic effects of mobile phone diffusion on

85   healthcare access in rural, resource-constrained areas. Empirically, it provides the first quantitative

86   evidence that the healthcare access of digitally excluded groups deteriorates with increasing mobile

87   phone diffusion, which challenges the framing of digital inclusion as an unproblematic process. The

88   tools and findings of this paper offer space for further research in other areas of digital development,

89   like employment, government service access, or social interaction.

90   The remainder of this paper situates the study in the fields of technology adoption and ICTD,

91   followed by a detailed description of the analytical framework (Section 2). Section 3 explains the

92   empirical model to analyse the household panel data from the IHDS, using fixed-effects linear

93   probability models with village-cluster robust standard errors to estimate households' probability to

94   access healthcare as a function of mobile phone adoption and district-level phone diffusion. The results

95   are described in Section 4, showing that households who failed to acquire a mobile phone between

96   2005 and 2012 are on average poorer, and that poor households without mobile phones are less likely

97   to gain access to "responsive" private healthcare providers if mobile phones have otherwise diffused

98   widely in their district. Taking into account limitations stemming from the household-level analysis,

99   the imposition of disease categories, and the representativeness of the panel data, Section 5 will argue

100   that the findings correspond to the analytical framework. The results suggest that, on the demand side,

101   diffusion drives competition and creates divides between poor phone users and non-users. On the

102   supply side, healthcare providers who are more responsive to patients' mobile phone use will

103   increasingly cater to this group at the expense of non-users. That public healthcare access is yet

104 unaffected by these trends should only offer momentary respite, given that my previous cross-sectional

105 study in 2013-2014 indicated that public providers in rural India have begun to adapt to patients'

106 mobile phone use, too. Section 6 concludes.

107 **2   Literature and Framework**

108 **2.1   Technology Diffusion, ICTD, and Digital Divides in the Context of Mobile Phones**

109 This paper speaks to the literature on digital divides and "information and communication

110 technologies and development" (ICTD) as part of the broader, interdisciplinary study of the social

111 implications of technology diffusion. Two key insights from the broader field—comprising

112 anthropological, sociological, and economic research—are that (a) technology diffusion has both

113 positive and negative consequences for social, economic, and political development; and that (b) these

114 implications are not evenly distributed. The anthropological and sociological literature suggests that

115 distributional variations stem partly from the coevolution between a technology and the society within

116 which it diffuses (Miller, 2010:53). This can entail unforeseen outcomes, as researchers have argued

117 for example that roads create rather than reduce the distance between people (Pedersen & Bunkenborg,

118 2012:565), clocks have become instruments of control and oppression (Munn, 1992:109; Thompson,

119 1967:81-86), and new water management technologies alienated previously collaborative communities

120 (Bédoucha, 2002:104).

121 Given the dialectic relationship between technology and society, it seems indeed improbable that

122 technology diffusion invariably leads to desired development outcomes like improved economic

123 security, education, or political participation (consider e.g. the human development index by the United

124 Nations Development Programme, consisting of income, education, and longevity; UNDP, 2014:160-

125 163). That not all technical change processes are "pro-poor" has been shown for instance by Gudeman

126 (1992:145), who illustrates how continuing innovation and technical change helps Guatemalan

127 households to generate savings and—potentially—profits in the local markets, but their lacking

128   bargaining power means that more competitive merchants absorb the surplus. And although the

129   broader economic literature of technology diffusion tends to be more enthusiastic about its potential

130   benefits (Bandiera & Rasul, 2006:869; Besley & Case, 1993:396; Foster & Rosenzweig, 2010:421),

131   it, too, is occasionally cognizant of nuances and absences of development outcomes (Stewart,

132   1978:74).

133   Within this field, ICTD research focuses on a subset of (typically digital) technologies and their

134   potential applications to support "development" (variously defined) in low- and middle-income

135   contexts (Díaz Andrade & Urquhart, 2012:289; Duncombe, 2012:2; Flor, 2015; Heeks, 2014:2; Unwin,

136   2009:1). As a result, most research in the area of ICTD has focused on ICT readiness and availability,

137   the factors that drive diffusion and acceptance of technologies, and the positive development potential

138   of technological change (Andersson & Hatakka, 2013:293; Dodson *et al.*, 2012; Heeks, 2014:12;

139   Qureshi, 2015:516; Roztocki & Weistroffer, 2014:351). This involves for example the development

140   and delivery of phone-based interventions in areas like personal finance (Jack & Suri, 2014:220),

141   agricultural marketing (Rashid & Elder, 2009:5-8), or learning (Aker *et al.*, 2012:118).

142   The techno-centric focus in ICTD has been criticised for its insufficient emphasis on the social

143   embeddedness of technology, user behaviour and different forms of use, unintended negative and

144   positive effects of ICT diffusion, the equity implications of technological change, and the broad

145   spectrum of consequences surrounding digital inclusion and exclusion (Ayanso *et al.*, 2013:63;

146   Graham, 2011; Heeks, 2014:12; Sæbø & Furuholt, 2013:128-130; Wyche, 2015:2). The field is only

147   now experiencing a gradual transition towards broader research of technological and social

148   development, a growing theoretical base, and more interdisciplinary and mixed-method research that

149   permits locally grounded conclusions—beginning thus to reflect concerns of the broader study of

150   technology diffusion (Andersson & Hatakka, 2013; Burrell & Toyama, 2009; Chib, 2015; Donner,

151   2015; Gagliardone, 2015; Heeks, 2009:27; Kleine, 2013; Walsham, 2013:50).

152   The sub-field of "digital divides" has made a similar transition. The digital divide literature

153   focuses on the uneven adoption of technology, which tends to reproduce or even reinforce inter-

154   personal and inter-societal inequities. Originally framed in terms of ownership of ICT—the "haves"

155   vs. the "have nots" (Barzilai-Nahon, 2006:270; Dewan & Frederick, 2005:299-300; Qureshi,

156   2014:215; Stump *et al.*, 2008)—the concept would eventually develop into "higher-order" forms of

157   actual engagement with ICTs together with the skills required for their operation (Barzilai-Nahon,

158   2006:274-275; Helsper, 2012:411-414; May & Diga, 2015:100; Pearce, 2013:78; Robinson *et al.*,

159   2015; van Dijk, 2006:224). Donner (2015:137-154), Graham *et al.* (2014:758-759), and Schroeder

160   (2015:2828-2830) go yet further and analyse digital divides between social groups and across countries

161   in terms of technology-aided media content creation and consumption.

162   While the potentially problematic equity outcomes of technology diffusion are increasingly

163   acknowledged (Mbiti & Weil, 2011:16-17), the process of inclusion is regarded as unproblematic and

164   adoption as generally desirable. For example, Donner, though critical of the distributional implications

165   of global mobile Internet diffusion, argues that, "When we assess the spread of informational

166   production via mobile devices we should not let the (absent) perfect be the enemy of the (nearly

167   ubiquitous) good" (Donner, 2015:153-154). It is thus assumed that diffusion processes benefit various

168   groups differently, but that no party involved in the process will see its living conditions worsen.

169   I investigate in this paper whether such a positive approach to digital inclusion is defensible.

170   In contrast to previous studies in the field of technology adoption and ICTD, my focus is in particular

171   on population groups who are *excluded* from the process of mobile phone diffusion. I consider the case

172   of healthcare access in resource-constrained contexts (health being an important domain of

173   development; Sen, 1999), specifically healthcare access in rural India between 2005 and 2012. I derive

174   my hypotheses from an analytical framework that is based on previous qualitative and quantitative

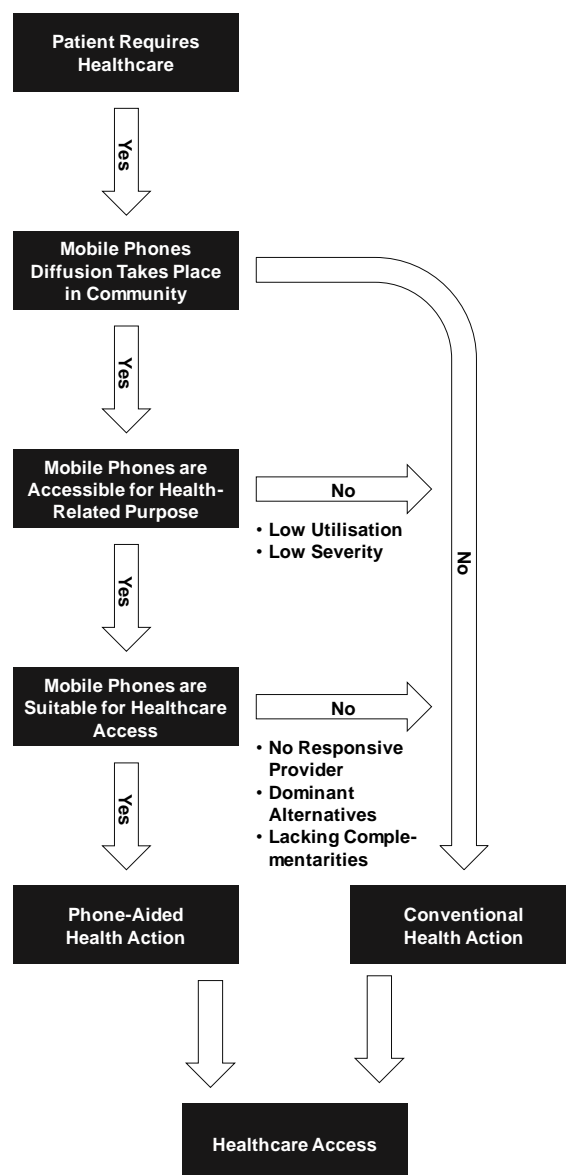175   research in rural India and rural China (Haenssgen, 2015a, 2015b, 2015c), described in the following

176   section.

177 ## 2.2 Analytical Framework

178 ### 2.2.1 Summary

179 In short, my framework explores the process of digital inclusion and suggests that, as mobile

180 phones diffuse, an already marginalised part of the rural population will be unable to incorporate

181 phones into their health behaviour. Those individuals who are able to do so will for example call a

182 doctor for a home visit or an appointment, have a family member arrange a taxi, or ask friends about

183 sensible treatment options. Within my framework, I expect that such activities entail a shift in patients'

184 healthcare access towards providers who are more capable of accommodating phone-aided behaviour

185 as part of their service delivery—in rural India, these "responsive" providers more are likely to be

186 private than public doctors as they are not bound to their clinic to carry out a home visit, for example.

187 If an increasing number of patients uses mobile phones in order to access healthcare providers, then

188 this will not only increase demand for healthcare (disregarding here as to whether such demand would

189 constitute an improvement, which it need not necessarily), but the health system will also progressively

190 adapt and cater to this behaviour (e.g. local doctors being only "on call"). Based on this framework, I

191 hypothesise that a health system which adapts to mobile phone use will discriminate increasingly

192 against marginalised and digitally excluded groups.

193 ### 2.2.2 Incorporating Phones Into Health Behaviour

194 The process of healthcare-related mobile phone use is depicted as a flow chart in Fig. 1. It

195 shows that, when a patient is ill and requires healthcare access, she will incorporate mobile phones

196 into her healthcare-seeking behaviour if these are generally available, if they are accessible for a health-

197 related purpose, and if they are a suitable solution for the problem at hand. Should these three

198 conditions not hold, the patient will engage in conventional health action without mobile phones. This

199 process is described in detail below.

200

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                    ┌─────────────────────┐
                    │  Patient Requires   │
                    │     Healthcare      │
                    └─────────────────────┘
                              │ Yes
                              ▼
                    ┌─────────────────────┐
                    │   Mobile Phones     │──────────────┐
                    │ Diffusion Takes Place│              │
                    │    in Community     │              │ No
                    └─────────────────────┘              │
                              │ Yes                       │
                              ▼                           │
                    ┌─────────────────────┐               │
                    │  Mobile Phones are  │── No ──▶       │
                    │ Accessible for Health-│              │
                    │   Related Purpose   │  • Low Utilisation
                    └─────────────────────┘  • Low Severity
                              │ Yes                       │
                              ▼                           │
                    ┌─────────────────────┐               │
                    │  Mobile Phones are  │── No ──▶       │
                    │ Suitable for Healthcare│             │
                    │      Access         │  • No Responsive
                    └─────────────────────┘    Provider    │
                              │ Yes          • Dominant    │
                              ▼                Alternatives │
                    ┌──────────────┐         • Lacking Comple-
                    │ Phone-Aided  │           mentarities  │
                    │ Health Action│        ┌──────────────┐◀
                    └──────────────┘        │ Conventional │
                           │                │ Health Action│
                           ▼                └──────────────┘
                                                   │
                           └───────┐      ┌────────┘
                                   ▼      ▼
                              ┌──────────────┐
                              │ Healthcare Access │
                              └──────────────┘
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201

Fig. 1. Stylised Description of Phone-Aided Health Action Decision-Making Process

203   Source: Author.
204

205   Even in contexts where mobile phones diffuse rapidly among individuals, households, and

206   communities, people will continue to exhibit diverse arrangements for accessing mobile devices,

207   which means that difficulties in utilising the technology are likely to remain (Burrell, 2010; Chipchase,

208   2006; Hampshire *et al.*, 2015:97-98; Hampshire *et al.*, 2011:707; Helsper, 2012:411; Karnowski *et al.*,

209   2011; Katz, 2008:10-11; Reisdorf *et al.*, 2012:15-16; Steenson & Donner, 2009). For example, to

210   "borrow" a mobile phone requires the explicit permission of the owner of the phone and may come

211   with explicit or implicit costs and obligations for the borrower. In this context, Hahn and Kibora (2008)

212   show that it is customary in Burkina Faso to summon remote family members for funeral arrangements

213   when a villager dies. Phones are borrowed for this purpose from teachers (among others) who live in

214   the village, but the teachers would in return "expect the young men from the village to weed their

215   field" (Hahn & Kibora, 2008:99), which highlights the reciprocal nature and implicit costs of phone

216   borrowing. Similarly, differences in personal characteristics, technical features, technological context,

217   social environment, and local cultures influence how people engage with mobile devices. For example,

218   different mobile phone types and specially designed devices for older users (audio aides, high-contrast

219   displays, simplified navigation) can remedy some of the challenges arising from age-related sensorial

220   impairment (Kurniawan, 2008:893-895; Ziefle & Bay, 2005:381-382).

221   Whether a phone is indeed accessible for health-related uses also depends on the severity of

222   the patient's health condition. Difficult access can rule out mobile phone use for what are perceived

223   "trivial" health reasons; common and mild conditions like colds or headaches may neither convince

224   lenders nor justify the social obligations for borrowers to ask for others' mobile phones. Less pressing

225   health issues, indirect and non-personal access, and less intensive and extensive usage can thus create

226   a disjunction between mobile phone diffusion and phone-aided health action.

227   Aside from being accessible for a health-related purpose, mobile phones also need to be a

228   suitable solution from the perspective of the patient. My notion of suitability has three interlinked

229   elements. Firstly, the actors and solutions within the health system need to be responsive to phone use,

230   which means that they can be accessed through the phone and provide desirable solutions from the

231   perspective of the patient. If actors in the patient's surrounding health system are not responsive,

232   accessing them via mobile phones may be futile and the patient has to find other solutions. For

233   example, Pitt and Pusponegoro (2005:145) report the need for emergency ambulance services

234   following a terrorist attack in Jakarta. As an ambulance called for an injured diplomat failed to arrive

235   in good time, "the casualty was taken to hospital in the nearest available form of transport—a rubbish

236   truck" (Pitt & Pusponegoro, 2005:146). While health system actors as in this case may be unable to

237   respond to mobile phone use, others may actively oppose it. This can have many reasons, including a

238   loss of income sources, concerns about workload, circumvention of institutionalised referral systems,

239   privacy, accountability, and personal safety during home visits (Mechael, 2006:169-170). And

240   although access to such unresponsive providers can also be coordinated without having to interact with

241   them directly (Nakahara *et al.*, 2010:323-325), we may expect that healthcare seeking through the

242   phone is more likely to be practised *along the lines of responsive actors in the health system*.

243   Secondly, where the health system can be navigated through viable alternatives to a phone-

244   aided solution, mobile phones are superfluous. Patients are arguably less likely to use a phone if they

245   have preferred health facilities in their immediate vicinity. The World Health Organization (WHO)

246   illustrates such substitutability through emergency care in Ghana: According to a recent report,

247   ambulance services can be accessed "by calling the dedicated emergency line (193) from landlines and

248   mobile phones. However, people can also walk to the ambulance station or make a radio announcement

249   through local FM stations" (WHO, 2010:9). Whether access is unproblematic is then partly a result of

250   availability and location of healthcare providers relative to the patient. Other factors contributing to

251   the substitutability between phone-aided and conventional healthcare access are personal

252   characteristics (e.g. ability to walk or cycle, immediate access to vehicles and caregivers in one's

253   household) and contextual conditions (e.g. safe roads in good condition, efficient and affordable public

254   transport), which can undermine the instrumental value a mobile phone during an illness. Besides,

255   patients may choose courses of action that are less likely to involve mobile phones, for example self-

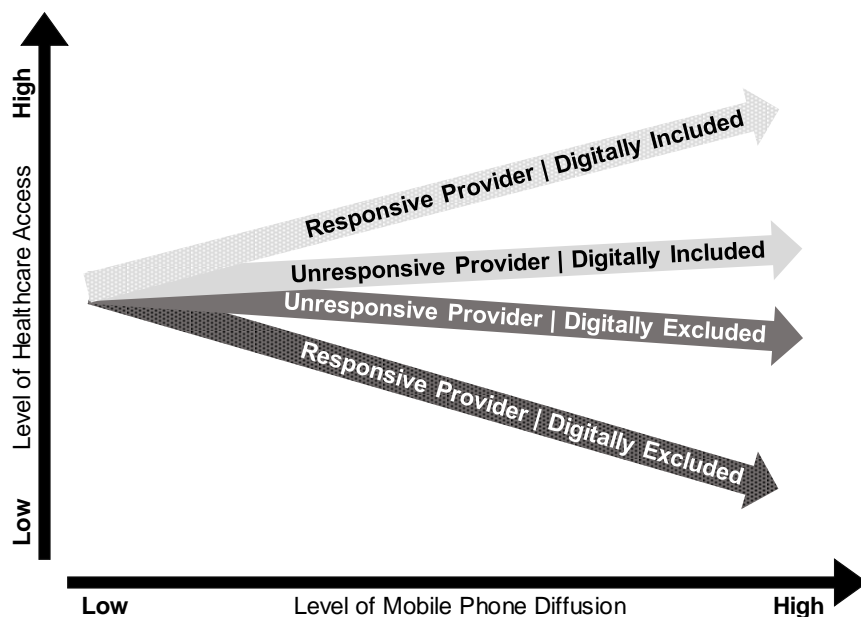256   treatment with medicines at home.

257   Thirdly, while some individual, contextual, and behavioural factors provide an alternative to

258   health-related phone use, others constitute complementarities that facilitate the realisation of certain

259   types of phone-aided healthcare seeking, for example proper road infrastructure enabling home calls.[2]

260   Some authors for instance suggest that complementary service networks such as taxis need to be

261 present to enable phone use for emergency transportation (Horst & Miller, 2006:140; Mechael,

262 2006:121-122; Miller, 2010:128). Likewise, favourable location, public transportation links, and

263 personal vehicle ownership described above as alternatives to home calls can also be facilitators to

264 other activities such as making appointments. While the interplay of alternative solutions and

265 complementarities shapes the visible spectrum of phone-aided healthcare solutions in a given context,

266 it is not clear *a priori* whether the presence or absence of specific assets like vehicles facilitates or

267 discourages phone-aided health action on average.

268 This process framework suggests that certain parties are possibly excluded from phone-aided

269 health action despite the apparent diffusion of these devices. Digital exclusion of this form is therefore

270 partly a matter of choice (if alternative solutions are dominant), but also of constraint (no phone

271 diffusion, no alignment between phone utilisation and health condition, no responsive provider). Pre-

272 existing patterns of economic, social, and spatial marginalisation can contribute to people falling into

273 the group of "constrained non-users."

274 **2.2.3   Equity Implications of Phone-Aided Health Action**

275 Fig. 2 considers the implications of the process framework for rural healthcare access. Overall,

276 if patients used to refrain from seeking care or relied on local yet unqualified healthcare professionals

277 *for want of better options*, then mobile phones might enable them to tap into a broader range of

278 solutions, provided that other actors are responsive. The responsiveness of the health system is

279 arguably a function of the diffusion of mobile phones and the associated use of phones among patients

280 for health-related purposes. The light-grey-shaded arrows in Fig. 2 illustrate this: The greater the extent

281 of mobile phone diffusion, the easier it is to use a mobile phone to gain direct access to responsive

282 healthcare providers. Even if a provider does not respond directly to mobile phone use, facilitated

283 logistical arrangements (e.g. taxis) can increase access as well, albeit to a lesser extent.

284

Fig. 2 shows four arrows emanating from a common origin point, labeled (from top to bottom):
- Responsive Provider | Digitally Included
- Unresponsive Provider | Digitally Included
- Unresponsive Provider | Digitally Excluded
- Responsive Provider | Digitally Excluded

The vertical axis is labeled "Level of Healthcare Access" (Low to High) and the horizontal axis is labeled "Level of Mobile Phone Diffusion" (Low to High).

285

Fig. 2. Hypothesised Relationship Between Healthcare, Mobile Phone Diffusion, Health Provider

Responsiveness, and Digital Inclusion of Patient

Source: Author.

286

287

288

289

290   An important implication of this framework is that dynamic health system changes in response

291   to increasing health-related phone use can leave non-users worse off than before, as illustrated by the

292   dark-grey-shaded arrows in Fig. 2. Imagine that a growing number of patients calls responsive doctors

293   to their homes for treatment (e.g. Mechael, 2006:169-170; 2008:98). These healthcare providers would

294   spend an increasing amount of time out of station, making it necessary for other patients to make

295   appointments prior to visiting the clinic. Non-users would consequently experience greater difficulty

296   in navigating the health system, finding "responsive" healthcare providers busy catering to phone users

297   or indeed out of station when they arrive at the clinic. Such developments need not be problematic for

298   individuals who previously had not used mobile phones because of dominant alternatives. As the

299   framework suggests, this group could incorporate phones because their relative value for healthcare

300   seeking rises. However, such developments would be problematic for those people who cannot use

301   mobile phones because of social, economic, or spatial marginalisation, thereby raising the barriers to

302   accessing healthcare. The ensuing depression of digitally excluded patients' access to responsive

303   healthcare providers is depicted in the bottom arrow in Fig. 2. To a lesser extent, this "crowding-out"

304   effect would also occur among digitally excluded patients accessing non-responsive providers. This

305   framework suggests that the process of digital inclusion creates an unequal struggle between those

306   patients who are able to use mobile phones to facilitate their healthcare access and those unable to do

307   so.

308   In summary, my theoretical framework problematizes the process of digital inclusion,

309   suggesting both positive and negative healthcare access patterns associated with mobile phone use and

310   risks of exacerbating the marginalisation of some groups. This is in contrast to the existing digital

311   inclusion narratives, which, even if the outcomes of complete diffusion are understood to be unequally

312   distributed, assume that the process itself is painless and unproblematic. Should it turn out that

313   diffusion instead undermines service access among the rural poor, then the mainstream narratives

314   might require revision.

315   **3   Materials and Methods**

316   This paper uses the case study of mobile phones and healthcare access in rural India (2005-

317   2012) to explore the social implications of diffusion and digital inclusion processes. I base my analysis

318   on recently published panel data from the nationwide Indian Human Development Survey for my

319   analysis (IHDS; Desai *et al.*, 2010b; Desai *et al.*, 2016). The IHDS was carried out in two waves in

320   2004-2005 and 2011-2012. Wave I included 41,554 households with 215,754 individuals; Wave II

321   surveyed 42,152 households with 204,569 individuals. The panel data structure in the IHDS allows for

322   the matching of households over the two survey periods, yet not of individuals. The analysis therefore

323   involves only those rural households that reported an illness in both survey periods in order to trace

324   healthcare choices over time; that is, 12,003 households per period across 22 Indian states.[3]

325   I estimate fixed-effects linear probability models with village-cluster robust standard errors,

326   which I explain in the remainder of this section. If healthcare access Y_{kit} is defined as household i's

327   probability of accessing healthcare provider k at time t, the empirical specification of the time-

328   demeaned fixed-effects model (with $t_1 = 2005$ and $t_2 = 2012$) is

329

330 $$\ddot{Y}_{kit} = \beta_m \ddot{MOB}_{it} + \beta_d \ddot{DIST}_{it} + \beta_x MOB\ddot{x}DIST_{it} + \beta CON\ddot{T}ROLS_{it} + YEAR_t + \ddot{u}_{it}, \qquad (1)$$

331

332   Where $\ddot{Y}_{kit} = Y_{kit} - \bar{Y}_{ki}$ etc. are time-demeaned variables; MOB_{it} is household-level mobile

333   ownership; $DIST_{it}$ is district-level mobile phone diffusion (as a proxy for health system adaptation to

334   mobile phone use); $MOBxDIST_{it}$ is an interaction term; $CONTROLS_{it}$ are other household-level, time-

335   variant variables controlling for healthcare access; $YEAR_t$ is a trend variable; and u_{it} is an idiosyncratic

336   error term. Because of time-demeaning (see below), household-specific and time-invariant

337   characteristics drop from the analysis (in the two-period case, the equivalent is achieved by

338   differencing between the survey periods). The dependent and independent variables in this model are

339   summarised in Table 1.

340

341   *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
Independent Variables	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

Other Control Variables	*MOBxDISTit* (Interaction Term)	Interaction term between household-level mobile phone ownership and district-level mobile phone diffusion rate
	HH Landline Phone	[1] if household owns at least one landline phone; [0] otherwise
	HH Highest Education	Highest completed grade of formal education of any household member; [0] if illiterate, [1] if uncompleted primary education, [2] if completed primary education (5th class), [3] if completed middle school (8th class), [4] if completed secondary education (10th class), [5] if completed higher secondary education (12th class).
	HH Average Sex	Percentage of women in household; [1] if 100% women
	HH Size	Number of members in household
	HH Average Age	Unweighted average age of all household members
	HH Below Poverty Line	[1] if per capita household expenditure < poverty line (which varies by state; 2005 poverty line adjusted by village-wise deflator); [0] otherwise
	HH Asset Index[a]	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.
	Major Illness	[1] if any household member experienced a "major" disease in last 12 months (e.g. cataracts, tuberculosis, hypertension); [0] otherwise
	Mild Illness	[1] if any household member experienced a "minor" disease in last 12 months (e.g. fever, cough/cold, diarrhoea); [0] otherwise
	No. of Public Health Facilities	Village-level count of public clinics (e.g. sub-centre, primary health centre, community health centre), as recorded in medical facility questionnaire
	No. of Private Health Facilities	Village-level count of private, as recorded in medical facility questionnaire
	No. of Other Health Facilities	Village-level count of other health facilities (e.g. family planning clinic), as recorded in medical facility questionnaire
	Year Dummy	Trend variable, capturing developments e.g. in local infrastructure and overall health service provision

342 Sources: Author, based on Beals (1976); Colson (1971); Gulliford *et al.* (2002); Kroeger (1983); Lieber *et al.* (2006); Meessen *et al.*
343 (2011); Nyamongo (2002); Shaikh *et al.* (2008); Shaikh and Hatcher (2005); Storla *et al.* (2008); van Egeren and Fabrega (1976); Ward
344 *et al.* (1997).
345 *Notes*: HH is household; defined as "people living under one roof and sharing the same kitchen" (Desai *et al.*, 2010a:222).
346 [a.] Wealth index includes mobile phones. Robustness checks excluding phones from index confirmed main results. Robustness checks
347 separating vehicles from wealth index have reproduced the model results without notable differences, while the vehicle coefficient was
348 statistically insignificant for all estimated models. The reported models therefore only include the wealth index.
349

350   This analysis involves the estimation of a healthcare access model, which includes mobile

351 phone adoption and diffusion among other determinants of access. Healthcare access takes place in a

352 broader health system, which I define in line with the WHO as a system that incorporates "all

353 organizations, people and actions whose primary intent is to promote, restore or maintain health"

354 (WHO, 2007:2). Access to public and private medical care providers are therefore not the only forms

355 of healthcare utilisation. Informal caregivers and traditional healers should also be considered in

356 healthcare access models, given that they account for up to 90% of all healthcare providers in the health

357   systems of some low- and middle-income countries (Sudhinaraset *et al.*, 2013:3). In order to appreciate

358   the multi-actor (or "pluralistic") nature of the rural Indian health system, the dependent variables I

359   consider access to public doctors and nurses, private clinics, pharmacists, and "traditional and other"

360   healthcare providers, together with overall access to any of these providers. In the empirical models,

361   these are dummy variables that indicate whether any member of the household with a "minor" or

362   "major" illness accessed the respective type of healthcare (conditional on an illness in the household

363   during the twelve months preceding each survey round).[4] Different types of access can take place for

364   the same household at the same time.

365   As I hypothesise that a health system that adapts to mobile phones will discriminate

366   increasingly against individuals who do not adopt mobile technology, the independent variables of

367   interest relate to household-level mobile phone adoption and health system adaptation to phone

368   diffusion. I use district-level mobile phone diffusion to approximate a state in which a health system

369   may expect people's mobile phone use to a greater or lesser extent. This variable is calculated as the

370   population-weighted percentage of households who own a mobile phone. In addition, the IDHS data

371   does not include patients' healthcare-related mobile phone use, but previous research has found that

372   the absence of household mobile phones predicts the absence of phone-aided healthcare-seeking better

373   than the absence personal phone ownership (Haenssgen, 2015b:8). I therefore use household-level

374   mobile phone ownership to approximate the likelihood of household members to engage in health-

375   related phone use. Household phone use and system adaptation may interact insofar as a person using

376   a mobile phone to access a doctor may be more successful in a system that expects such phone use

377   (e.g. by calling taxis, by doctors being ready to accept calls on their mobiles). The interaction term

378    $MOBxDIST_{it}$ captures this relationship.

379   A positive evaluation of the hypothesis follows if (a) healthcare-related mobile phone use

380   contributes to better access to healthcare, (b) increasing health system adaptation has a negative effect

381   on healthcare access, and (c) the coefficient of the interaction between health-related phone use and

382   system adaptation is positive, meaning that mobile phone ownership becomes increasingly useful and

383   compensates for the otherwise adverse effects of system adaptation. However, the analytical

384   framework points at space for heterogeneity, as adverse effects may be particularly pronounced for

385   poor households who do not have alternative means of accessing healthcare. In addition, we may

386   expect heterogeneity across different types of healthcare providers, with smaller effects for public

387   providers such as regional hospitals that are bound by institutionalised referral systems and guidelines

388   that prevent phone-based service delivery (Mechael, 2006:169-170).

389   The empirical model controls for other determinants of access, based on the literature on

390   healthcare seeking and therapeutic itineraries. Important determinants of healthcare access in this

391   literature are the nature, severity, and stage of the specific health condition; the patient's education,

392   economic situation, age, sex, and decision-making autonomy; personal predispositions and belief

393   systems (e.g. accepting pain as part of lifestyle); societal perceptions of the health condition;

394   availability, accessibility, and awareness about providers (e.g. location); trust in and perceptions of the

395   providers' quality of care; and the compatibility of provider competences with the patient's condition

396   (Beals, 1976:184-185; Colson, 1971:234-236; Kroeger, 1983:149; Lieber *et al.*, 2006:469; Nyamongo,

397   2002:381; Shaikh *et al.*, 2008:749-753; Shaikh & Hatcher, 2005:50-52; van Egeren & Fabrega,

398   1976:537-538; Ward *et al.*, 1997:21-23).

399   This long list of determinants suggests that an empirical analysis of healthcare access should

400   be cognisant not only of mobile phone diffusion but also of the patient's characteristics, her or his

401   social networks and cultural environment, the nature of the illness, and health system attributes. Table

402   1 displays and describes the control variables that approximate these factors within the IHDS data set.

403   However, it is plausible that unobserved characteristics like health provider preferences are not

404   captured with the IHDS data. In such a case, the error term ε_{it} in an empirical model could be specified

405   with an idiosyncratic and a household-specific, time-invariant component: $\varepsilon_{it} = a_i + u_{it}$. If the

406   unobserved household characteristics were correlated with other predictor variables, then this would

407   be a case of an omitted variable problem.

408   I choose fixed-effects models in order to deal with this problem because, through time-

409   demeaning, the unobservable (assumed static) household characteristics $\ddot{a}_i = a_i - \bar{a}_i$ drop from the

410   model, leaving only the idiosyncratic error term $\ddot{u}_{it} = u_{it} - \bar{u}_i$. Hausman and generalised Hausman tests

411   were statistically significant at the 0.1-percent level for all but two of the estimated models (two

412   affluent sub-sample estimations were statistically significant at the one-percent level), indicating that

413   the fixed-effects specification is preferable to random effects panel models that treat unobserved as

414   uncorrelated with other independent variables.

415   Because the dependent variable is not normally distributed, logistic regression models are

416   typically preferable to model binary access to healthcare. However, the fixed-effects estimator in a

417   panel logit regression model is likely to be inconsistent where only few time periods are considered—

418   two in the present case (Greene, 2008:801). Considering the problem of inconsistent estimation, I

419   report in this paper only linear probability models with village-cluster robust standard errors

420   (estimations with serial-correlation- and heteroscedasticity-robust standard errors yielded less

421   conservative results and will be omitted here). Robustness checks using fixed-effects logit models

422   yielded results that generally point in the same direction, although significance levels are weakly

423   sensitive to functional form.

424   Furthermore, it could be argued that the panel containing ill households introduces a sample

425   selection bias. However, the estimation sample containing only sick households in 2005 and 2012 is

426   remarkably similar to the complete panel of rural Indian households, for example in terms of household

427   size (it is on average by 0.3 members smaller in 2005; by 0.2 in 2012) and wealth (on average by 0.10

428   index units wealthier on a scale from 0 to 33 in 2005; by 0.17 in 2012).[5] In addition, it is plausible to

429   assume that any unobserved household characteristics leading to inclusion into the estimation sample

430   are controlled for by the fixed-effects estimator. I carried out the analysis using Stata 13 (StataCorp,

431   2013).

4   Results

4.1   Context and Descriptive Statistics

434   In order to prepare the multivariate analysis, this section presents descriptive statistics using

435   the IHDS survey sample of households who experienced illnesses in both survey rounds. Summary

436   statistics of this sample are presented in Table 2.

437 *Table 2. Summary Statistics of Survey Sample: 2005, 2012, and First Difference*

	Round I: 2005					Round II: 2012					First Difference 2005-2012				
	n	Mean	Std. Dev	Min	Max	*n*	Mean	Std. Dev	Min	Max	*n*	Mean Diff.	Std. Dev	Min Diff.	Max Diff.
HH Mobile Phone	12,003	0.03	0.17	0	1	12,003	0.75	0.43	0	1	12,003	+ 0.72	0.45	− 1	+ 1
District Phone Diffusion[a]	264	0.03	0.05	0.00	0.33	264	0.73	0.18	0.00	0.99	12,003	+ 0.70	0.16	0.00	+ 0.95
HH Landline Phone	12,003	0.11	0.31	0	1	12,003	0.05	0.22	0	1	12,003	− 0.06	0.30	− 1	+ 1
HH Size	12,003	6.38	3.25	1	33	12,003	5.14	2.52	1	33	12,003	− 1.24	3.27	− 24	+ 26
HH Highest Education[b]	12,003	1.97	1.53	0	5	12,003	2.15	1.56	0	5	12,003	+ 0.18	1.30	− 5	+ 5
HH Average Sex (1=Female)	12,003	0.49	0.16	0.00	1.00	12,003	0.51	0.18	0.00	1.00	12,003	+ 0.02	0.16	− 0.75	+ 1.00
HH Average Age	12,003	28.23	10.89	8.00	90.00	12,003	31.95	13.79	6.80	99.00	12,003	+ 3.72	11.15	− 59.40	+ 58.00
HH Below Poverty Line[c]	12,003	0.22	0.41	0	1	12,003	0.19	0.39	0	1	12,003	− 0.03	0.50	− 1	+ 1
HH Asset Index[d]	12,003	9.68	5.14	0	27	12,003	12.49	5.73	0	28	12,003	2.81	3.68	− 15	+ 21
Experienced Any Illness	12,003	1.00	0.00	1	1	12,003	1.00	0.00	1	1	12,003	+ 0.00	0.00	0	0
Accessed Any Healthcare	12,003	0.96	0.19	0	1	12,003	0.97	0.16	0	1	12,003	+ 0.01	0.25	− 1	+ 1
Accessed Public Care	12,003	0.31	0.46	0	1	12,003	0.34	0.47	0	1	12,003	+ 0.04	0.58	− 1	+ 1
Accessed Private Care	12,003	0.69	0.46	0	1	12,003	0.72	0.45	0	1	12,003	+ 0.03	0.58	− 1	+ 1
Accessed Pharmacist	12,003	0.06	0.23	0	1	12,003	0.08	0.28	0	1	12,003	+ 0.03	0.36	− 1	+ 1
Accessed Traditional/Other Care	12,003	0.03	0.16	0	1	12,003	0.04	0.19	0	1	12,003	+ 0.01	0.24	− 1	+ 1
Minor Illness in Past 12 Months	12,003	0.83	0.38	0	1	12,003	0.80	0.40	0	1	12,003	− 0.03	0.51	− 1	+ 1
Major Illness in Past 12 Months	12,003	0.43	0.50	0	1	12,003	0.56	0.50	0	1	12,003	0.13	0.65	− 1	+ 1
No. of Public Clinics[e]	1266	0.89	0.35	0	2	1325	0.90	0.32	0	2	1266	0.01	0.44	− 2	+ 1
No. of Private Clinics[e]	1266	0.93	0.33	0	3	1325	0.86	0.35	0	2	1266	− 0.06	0.45	− 2	+ 1
No. of Other Clinics[e]	1266	0.09	0.30	0	2	1325	0.07	0.26	0	2	1266	− 0.02	0.39	− 2	+ 2

(The rows "Experienced Any Illness" through "Accessed Traditional/Other Care" are grouped under the side label: "Any HH Member, for Any Illness")

438 *Notes:* Unweighted statistics. First difference morbidity statistics for households who experienced a minor/major illness in both survey rounds. HH is household.
439 [a] 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.
440 [b] 0="illiterate," 1="uncompleted primary education," 2="completed primary education (5th class)," 3="completed middle school (8th class)," 4="completed secondary education (10th class)," 5=
441 "completed higher secondary education (12th class)."
442 [c] 1 = per capita household expenditure < poverty line (which varies by state; 2005 poverty line adjusted by village-wise deflator).
443 [d] Unweighted sum of 33 household assets, using the same household asset categories in 2005 and 2012.
444 [e] Village-level data, as recorded in medical facility questionnaire.

445   As is evident from the table, mobile phones have spread rapidly across rural India

446   between 2005 and 2012. The average share of households owning a phone in the sample has

447   increased from 3% to 75% over the study period from 2005 to 2012. An average district in the

448   study sample experienced an increase of 70 percentage points in the absolute proportion of rural

449   households owning a mobile phone, with an inter-quartile range of 62-81% (a histogram

450   depicting the increase is shown in Fig. 3). At the same time, the share of households owning a

451   landline phone dropped from 11% to 5%.

452
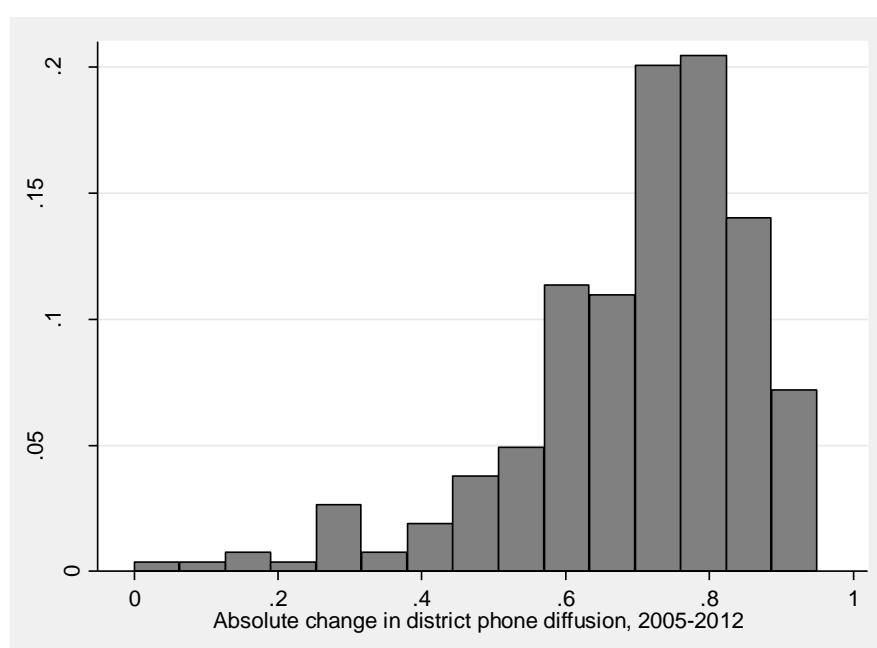
Fig. 3. Change in District-Level Mobile Phone Diffusion in Survey Sample, 2005-2012

458   Other socioeconomic indicators also indicate notable change over time. For example,

459   the average survey household became smaller and was 3.7 years older in the second survey

460   round. Wealth increased by 29% from 9.7 to 12.5 common household items, and the share of

461   households below the poverty line fell 3 percentage points (based on inflation-adjusted state-

462   level poverty lines and per-capita household expenditure).

463   In terms of healthcare, overall utilisation rates of informal and formal healthcare

464   providers were very high with 97% in 2012, up 1% from 2005. Private healthcare was with

465   71% in 2012 the most commonly accessed type among the rural households in the survey, while

466   traditional and other forms of healthcare provision only accounted for 4% of the sample in 2012.

467   Access to all categories of healthcare providers increased between 1 (traditional healers) and 4

468   (public doctors) percentage points over the two study periods. As far as the supply of health

469   facilities is concerned (considering that IHDS does not contain an exhaustive census of health

470   facilities), village-level facility survey data from the IHDS indicates that the provision of public

471   clinics increased slightly from an average of 0.89 to 0.90 facilities per village (corresponding

472   to a decrease from 12.0% to 10.6% of villages without any public clinic). Private facilities were

473   commonly found in the survey villages as well but their average number (together with "other"

474   clinics e.g. for family planning) fell marginally over the same period. Overall, the survey

475   context is one in which households experienced a notable increase in socio-economic

476   indicators, situated in an environment of high healthcare demand and constant supply.

477   The analysis in the remainder of this paper will make the claim that mobile phone

478   diffusion has undermined healthcare access for marginalised groups at the expense of more

479   affluent households. In order to establish that mobile phone owning households are better off

480   than their "disconnected" peers, Table 3 presents the levels and changes of household assets

481   and poverty status, depending on whether a household owned a mobile phone in 2005 and 2012.

482   The table shows that households who did not own a phone in either period had the highest

483   poverty incidence and the lowest wealth, the latter of which expanded below the sample

484   average. In contrast, households who acquired a phone between 2005 and 2012 developed their

485   asset wealth by 3.7 units (2.7 if adjusted for mobile phones as index component), notably above

486   the sample average of 2.8 (2.1). In light of these patterns, we can establish that households who

487   had not acquired a mobile phone by 2012 were economically more marginalised than those who

488   did.

489

490   *Table 3. Wealth and Poverty Trends by Household Mobile Phone Ownership*

Phone in 2005	Phone in 2012	Number of Households in Panel	Average Household Asset Index			% of Households < Poverty Line		
			2005 (adjusted)[a]	2012 (adjusted)[a]	Difference (adjusted)[a]	2005	2012	Difference
Yes	No	22 (0.2%)	16.5 (15.5)	11.9	− 4.6 (− 3.6)	0.0%	18.2%	+ 18.2%
No	No	2,987 (24.9%)	6.6	7.2	+ 0.6	33.8%	33.1%	− 0.7%
Yes	Yes	340 (2.8%)	19.7 (18.7)	20.6 (19.6)	+ 0.9	1.5%	4.4%	+ 2.9%
No	Yes	8,654 (72.1%)	10.3	14.0 (13.0)	+ 3.7 (+2.7)	18.9%	14.3%	− 4.6%
Total		12,003	9.7 (9.7)	12.5 (11.7)	+ 2.8 (+2.1)	22.1 %	18.7%	− 3.3%

491   *Notes:* Unweighted statistics.
492   [a.] Household mobile phone ownership is a component of the household asset index. Acquiring the first household phone
493   corresponds to a one-unit increase in the index.

4.2   Regression Results

494   This section presents the results of the fixed-effects linear probability models. As

496   indicated in Section 3, I estimate 15 models, five each for the general rural population of India,

497   for rural households below median income ("poor"), and for rural households above the median

498   income ("affluent"). For each group, I estimate a model of overall access to any healthcare

499   provider, and provider-specific models for access to public doctors, private doctors,

500   pharmacists, and to traditional and other healthcare providers. The main independent variables

501   in these models are household-level mobile phone ownership, district-level mobile phone

502   diffusion, and an interaction term between these two variables. The linear probability model

503   results are shown in Table 4, all of which are significant at the 0.1-percent level. I focus the

504   examination of the results on overall access to healthcare and access to public and private

505   providers among poor households, which represent the most common forms of healthcare

506   utilisation.

507 *Table 4. Fixed-Effects Linear Probability Regression Results: Factors Influencing Change in Rural Healthcare Access*

	All Rural Households					Poor Households (<Median Wealth)[a]					Affluent Households (>Median Wealth)[a]				
	Any Healthcare	Public Care	Private Care	Pharmacists	Traditional / Other Care	Any Healthcare	Public Care	Private Care	Pharmacists	Traditional / Other Care	Any Healthcare	Public Care	Private Care	Pharmacists	Traditional / Other Care
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
HH Mobile Phone	-0.02	0.05	-0.05	0.01	0.02	-0.07	0.07	-0.16*	-0.02	0.05	-0.01	0.03	-0.02	0.03	0.00
District Phone Diffusion	-0.10**	0.06	-0.12	-0.13**	-0.03	-0.15*	0.05	-0.19*	-0.13**	-0.03	-0.05	0.16	-0.05	-0.15*	-0.03
MOBxDIST Interaction	0.03	-0.09	0.11*	-0.02	-0.04	0.10	-0.10	0.28**	0.01	-0.07	0.00	-0.09	0.07	-0.01	-0.05*
HH Landline Phone	0.00	0.05**	-0.04	-0.02	-0.01	-0.03	0.04	-0.05	0.05	-0.03	0.00	0.05*	-0.04	-0.01	-0.01
HH Highest Education	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	-0.01	0.00	0.00
HH Size	0.00	0.00	0.00	0.00	-0.00**	0.00	0.00	0.01*	0.00	-0.00**	0.00	0.01*	0.00	0.00	0.00
HH Average Sex (% Female)	-0.04*	-0.02	-0.08*	0.05**	0.02	-0.03	-0.05	-0.05	0.06*	0.02	-0.04*	0.02	-0.11*	0.05	0.01
HH Average Age	0.00	0.00	-0.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00**	-0.00*	0.00	0.00
HH Below Poverty Line	-0.01	0.01	-0.05***	-0.01	0.01	-0.01	0.01	-0.05***	-0.01	0.02	-0.01	0.02	-0.05*	0.00	0.00
HH Asset Index	0.00	-0.01***	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01***	0.00	0.00	0.00
Minor Illness in Last 12m	0.07***	0.08***	0.16***	0.06***	0.02***	0.10***	0.06**	0.18***	0.07***	0.03***	0.05***	0.09***	0.15***	0.06***	0.01*
Major Illness in Last 12m	0.02***	0.12***	0.13***	0.04***	0.03***	0.03***	0.13***	0.12***	0.04***	0.03***	0.01**	0.11***	0.14***	0.04***	0.03***
No. of Public Clinics	0.00	-0.03	0.00	-0.02	0.02*	0.00	-0.05	-0.01	-0.03	0.04	0.00	-0.02	0.00	0.00	0.01
No. of Private Clinics	0.01	-0.02	0.04	0.03*	0.00	0.02	-0.01	0.05	0.02	0.00	0.01	-0.03	0.04	0.03	0.00
No. of Other Clinics	-0.01	0.02	0.00	-0.04*	0.00	0.00	0.05	0.00	-0.06**	0.02	-0.01	0.00	0.00	-0.02	-0.02
Year 2012 Dummy	0.08	0.02	0.06	0.11***	0.04	0.11	0.02	0.12	0.11**	0.03	0.05	-0.05	0.01	0.11*	0.06*
Constant	0.81	0.23***	0.45***	-0.14***	-0.06	0.73	0.24*	0.34***	-0.14**	-0.05	0.88	0.27**	0.56***	-0.12*	-0.07*
Number of Observations	24,006	24,006	24,006	24,006	24,006	12,672	12,672	12,672	12,672	12,672	11,334	11,334	11,334	11,334	11,334
R^2 (Within)	0.03	0.02	0.03	0.02	0.01	0.04	0.03	0.04	0.02	0.01	0.02	0.02	0.03	0.02	0.02
Model Test ($p > F$)	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000	<0.000

508
509
510

Notes: HH is household.

[a.] "Poor" and "affluent" categorised as below/above median wealth index, using average unweighted household wealth between both survey periods.

*$p<0.05$, **$p<0.01$, ***$p<0.001$.

511   The results allow three main observations. First, the table shows that mobile phone diffusion is

512   associated with changes in overall healthcare access (general population and poor sub-sample), private

513   healthcare access (general population and poor sub-sample), access to pharmacists (general population

514   and both sub-samples), and access to traditional and other healthcare providers (affluent sub-sample).

515   Public healthcare access appears to be independent of mobile phone diffusion on the household and

516   district levels, and the relationship between mobile phones and healthcare access appears to be weaker

517   for affluent households. These differences across healthcare providers, and especially the response of

518   private clinics, corresponds to my argument that some actors in the health system are more responsive

519   to mobile phone use.

520   Secondly, poorer households show a negative link between district-level mobile phone

521   diffusion and overall healthcare utilisation (Model 6, significant at the five-percent level) and access

522   to pharmacists (Model 9, significant at the one-percent level). The regression coefficients suggest that

523   a 10 percentage point increase in district-level mobile phone diffusion is linked to a 1.5 and 1.3

524   percentage point decrease in overall healthcare and pharmacist access for the poor household sub-

525   sample (1.0 and 1.3 percentage point decrease for the overall sample). The relatively weaker effect for

526   the affluent subsample corresponds to my notion that richer households have more means to access

527   healthcare, which reduces their need for mobile phones and insulates them from potentially adverse

528   consequences.

529   Thirdly, the effect of district-level mobile phone diffusion on poor household's access to

530   private clinics varies depending on whether a household owns a mobile. The interaction term in Model

531   8 is statistically significant at the one-percent level. As the interaction term is positive while the

532   coefficients of the interacting variables are both negative, the results indicate that the negative

533   relationship between private healthcare access and household-level mobile phone diffusion becomes

534   "more positive" as mobile phones diffuse more widely in the district. In addition, the effect of a

535   household mobile phone is initially negative, but higher degrees of district-level diffusion have a

536   positive effect for households owning mobile phones, leading to a combined effect that gradually

537   increases and exceeds households without mobile phones at approximately 57% district-level

538   diffusion. However, any linear combination of the coefficients remains negative (numerically, it would

539   only turn positive if around 180% of a district's households had acquired a phone). These patterns

540   correspond to the hypothesised idea that the value of using a mobile phone changes in a system that

541   adapts to such use (see the discussion in Section 5 why the average effect could be negative).

542   As far as other control variables are concerned,[6] the coefficient for landline phones suggests

543   that households seek more access to public doctors if their household acquires a landline phone

544   connection. But we also need to appreciate that the portion of households owning a landline phone

545   decreased from 11% to 5% across the study periods, and that landlines are less likely to be installed in

546   remote locations, so the coefficients indicate that a household is less likely to access public healthcare

547   if it loses its landline connection. For poorer households, with the exception of disease severity and

548   the constant term, none of the control variables for public healthcare access are significant at the five-

549   percent level. Aside from mobile phones, growing households and those surpassing the poverty line

550   become more likely to access private healthcare.

551   In order to explore the relevance of these results, it is instructive to compare the predicted

552   effects of mobile phone diffusion across all rural households and the poor sub-sample. For example,

553   linear predictions based on Models 1 and 6 suggest that an increase of district-level mobile phone

554   diffusion from 25% to 75% corresponds to a decrease in any kind of healthcare access from 98% to

555   93% for all rural households that experienced an illness, and from 96% to 90% for poor households.

556   Access to pharmacists would decrease from 9% to 3% for both groups in these scenarios.

557   The relationship between private healthcare access and mobile phone diffusion is less

558   straightforward, due to the interaction term. For the sample of all rural households, the linear

559   predictions suggest that a household without a mobile phone would see its probability to access a

560   private doctor decrease from 70.5% in a district with 25% diffusion to 64.8% in a district where 75%

561   of households own a phone. In contrast, a household with a mobile phone would see its probability

562   virtually unchanged at 68.6%. The differences are yet more pronounced for poor households, where a

563   similar expansion of district-level mobile phone diffusion would be associated with a decrease from

564   70.0% to 60.3% for households without mobile phones, and an increase from 60.9% to 65.1% for

565   households who own a mobile.

566   Fig. 4 visualises the predicted probability of a household to access private doctors (y-axis),

567   depending on household wealth (Panel a for all rural households, Panel b for poor households), on

568   household-level mobile phone ownership (dark-grey markers for households without, light-grey

569   markers for households with mobile phones), and on the extent to which mobile phones have diffused

570   on the district level (x-axis). The predictions indicate that households without mobile phones have

571   decreasing access to private doctors in districts where mobile phones have diffused more widely, and

572   this decrease is particularly pronounced for the poor rural households in Panel b. In contrast, the

573   probability of access is independent of diffusion rates if the household has a mobile phone—which

574   could mean that owning a mobile phone helps to prevent a deterioration in access—and a poor

575   household with a mobile phone is increasingly likely to access healthcare if phones have diffused more

576   widely.

577

578

579   *Fig. 4. Predicted Access to Private Healthcare by Phone Ownership and Household Wealth*

580   Source: Author, derived from Desai *et al.* (2010b, 2016).
581   *Notes:* Prediction based on fixed-effects linear probability models for households with private healthcare access in either survey round
582   (Table 4, Models 3 and 8). Vertical lines indicate 95%-confidence interval.
583

584   Overall, these results support the hypothesis that non-users of mobile phones have less access

585   to healthcare in contexts where mobile phones have diffused rapidly. Poor households' access to

586   overall healthcare, to private doctors, and to pharmacists is negatively linked to mobile phones

587   diffusion either on the district level or personal level. In contrast, affluent rural households' healthcare

588   access is largely independent of these developments.

589   **5   Discussion**

590   While I have already hinted at a possible interpretation of the results in the previous section, it

591   is important to consider at least three important limitations of the analysis before discussing its

592   significance. These limitations pertain to the imposition of disease severity classifications, the

593   representativeness of the panel data, and the level of analysis and its associated measurement

594   challenges.

595   Firstly, it could be considered problematic that the severity of illness, which controls for

596   households' healthcare access, is defined by the survey agency rather than by the respondents

597   themselves. Individuals' initial decisions to seek care are more likely to be driven by their

598   own observations and socially agreed notions of appropriate health action than by later diagnoses by

599   doctors and researchers (Beals, 1976:184-185; Gulliford *et al.*, 2002:187). While this may skew the

600   predictive power of control variables for "minor" and "major" illnesses, they remain statistically

601   significant and improve model fitness. Robustness checks that replaced binary disease severity

602   indicators with the number of household members with "minor" and "major" illnesses did not affect

603   the results.

604   Secondly, the panel is not a representative sample of all rural Indian households over time, but

605   rather of those whose members experienced illnesses repeatedly across the survey periods. The panel

606   structure used in this study enables an analysis of how households with sick members change their

607   behaviour in a dynamic mobile diffusion context, but it leaves open the question as to how an "average"

608   household would behave, given that only 60.2% of the household sample reported an illness in 2005,

609   and 71.7% in 2012. For example, mobile phone may enable some people to recognise a discomfort as

610   an illness (or vice versa). Nevertheless, average household characteristics of the full rural sample are

611   similar to the panel of ill households (see Section 3), and the household-fixed-effects analysis controls

612   for unobserved, time-invariant household characteristics. This makes it plausible that deviations from

613   average rural household behaviour in India are minor.

614   Lastly, and perhaps most importantly, the panel data of the IHDS only permits a household-

615   level analysis of healthcare access and mobile phone use, which limits the depth of the analysis. In the

616   present case, household-level healthcare access as a binary variable obscures the potentially sequential

617   logic of healthcare-seeking behaviour (Balabanova & McKee, 2002; Kibadi *et al.*, 2009; Moshabela

618   *et al.*, 2011; Shaikh *et al.*, 2008), the nature of potentially collective healthcare decision-making

619   (Peglidou, 2010:49), and, as a variable of "revealed behaviour," only captures successful access and

620   ignores whether an individual "sought" but failed to obtain healthcare. Likewise, household-level

621   mobile phone ownership maps only imperfectly onto individuals' actual health-related use of a mobile,

622   be it directly by the patient or mediated through a third person. In this respect, approximating health-

623   related mobile phone use through household phone ownership (or, more precisely, approximating the

624   absence of such use through the absence of a household mobile; Haenssgen, 2015b:8) also creates the

625   impression that very few non-users remain at near-100% district-level diffusion, which need not

626   necessarily be the case. Although these complications mean that the estimated models are only an

627   imperfect representation of the actual relationship between healthcare access and phone usage, I am

628   nonetheless able to discern effects that are consistent with the empirically grounded hypothesis that

629   non-users of mobile phones are worse off in contexts of fast diffusion. However, a more fine-grained

630   analysis would require higher-frequency panel survey data geared specifically towards individuals'

631   health-related mobile phone use and health system actors' capacity to absorb the demand from phone-

632   using patients.

633   In light of this discussion, considering that the linear probability models control for unobserved

634   heterogeneity while focusing on the change within households, and given that the panel regression

635   results correspond to hypotheses and findings derived from primary rural Indian survey data

636   (Haenssgen & Ariana, 2015), I have reason to trust the robustness of the results and the causality

637   running from changes in household- and district-level mobile phone adoption to households'

638   healthcare access. The identified relationship between district-level mobile phone diffusion and

639   household-level healthcare access suggests that health systems adapt to increasing mobile phone use,

640   which gradually improves the effect of a household mobile phone for rural households' access to

641   private healthcare. In the absence of a household mobile phone, poor households in districts with fast

642   mobile phone diffusion are less likely to access such healthcare. I see this as evidence that rapid mobile

643   phone diffusion can reinforce rather than ameliorate existing patterns of marginalisation, given that

644   digitally excluded households tend to be poorer on average.

645   Drawing on the initial explanatory framework, the findings can be explained through factors

646   on the demand as well as the supply side. On the demand side, mobile phone use appears to contribute

647   to healthcare access, enabling for example the ability to arrange home visits of doctors, to make

648   appointments, call a taxi, or simply to talk with relatives about treatment options (note that increased

649   access need not entail improved health outcomes). Not all but some households will make use of this

650   option, especially if it is the dominant strategy compared to alternative solutions, such as walking for

651   half an hour to a health post. Where such dominant phone-aided strategies among otherwise access-

652   constrained poor households exist, they increase their competitiveness relative to poor households

653   without mobile phones. This would bear resemblance to patterns observed in other contexts, for

654   instance the UK middle class reportedly exercising their "sharp elbows" towards other health system

655   users and thereby contributing to the reinforcement of healthcare inequities vis-à-vis poorer and more

656   vulnerable population groups (Seddon, 2007:88). Mobile phone users would therefore increasingly

657   join the "healthcare middle class," which is populated customarily by more affluent rural households

658   who face fewer healthcare access constraints and a wider range of choices, both of which insulate them

659   from the effects of mobile phone adoption and diffusion. As the data suggest, poor mobile phone users

660   gravitate towards the rural average level of private healthcare access in situations where phones have

661   diffused widely. The group losing the competitive struggle comprises households who are prevented

662   from adopting mobile technology. On the demand side, mobile phones therefore appear to create new

663   divisions and emerge as a somewhat regressive tool that benefits the "better-off" poor rural population.

664   The demand-side reactions interact with developments on the healthcare supply side. In

665   particular, the improved effects of phone ownership in contexts of fast mobile phone diffusion suggests

666   that health systems adapt to increasing mobile phone use and thus privilege phone-aided healthcare-

667   seeking strategies. But not all elements of the health system react equally to these developments. Public

668   health service access has not been affected, thanks probably to variations in responsiveness across

669   different health system actors. However, this may soon change, as my qualitative and quantitative

670   research in rural Rajasthan in 2013 and 2014 has indicated that local public doctors and nurses (based

671   in sub-centres and primary health centres) increasingly use mobile phones in their everyday work

672   (Haenssgen, 2015c). Flexible working conditions for local government providers (e.g. nurses and

673   village doctors) and gradually evolving guidelines that encourage health centre staff to deal with

674   patients' mobile-phone-aided healthcare behaviour suggest that public healthcare might not be

675   protected from patients' competitive pressure for much longer.

676   Although these findings correspond to my analytical framework, a remaining puzzle is the

677   average negative effect of mobile phone diffusion on healthcare access. A possible interpretation of

678   this pattern may be related to social capital. Qualitative and quantitative sociological research around

679   the world, which has made the claim that mobile phones enable people to uphold relationships with

680   close contacts with "strong" ties, but that they do not necessarily lead to more communication among

681   networks with "weak" ties and that they may even enable people to avoid their immediate social

682   environment (Horst, 2006:147-148; Ling, 2008:106; Miritello *et al.*, 2013:93-94; Saramäki *et al.*,

683   2014:946). Accordingly, mobile phones might enable rural Indian villagers to maintain relationships

684   with family members and close social contacts across villages, but these improvements come at the

685   expense of eroding local social capital. If this argument holds, then phone diffusion might reduce

686   people's ability to find help locally. However, because this explanation was not part of my framework

687   and cannot be tested with the present data set, it remains speculative and subject to further research.

688   Taken together, this is a considerable challenge for common narratives of digital inclusion. As

689   one group increasingly "benefits" from mobile phone use and an adapting environment, another loses

690   because healthcare supply does not pick up accordingly. This group—already poor—becomes

691   increasingly marginalised in contexts of otherwise rapid mobile phone diffusion. Indeed, during the

692   process of diffusion, one may *have to* become digitally included in order to maintain the same relative

693   position in healthcare access. At the same time, where mobile phones have not diffused rapidly,

694   acquiring one need not necessarily mean better access to services if the service providers are not

695   responsive to phone use.

696   **6   Conclusion**

697   Challenging the framing of "digital inclusion" as an unproblematic process, this paper explored

698   the relationship between mobile phone diffusion and rural Indian households' access to healthcare.

699   Based on previous research in rural India, I hypothesised that households without mobile phones are

700   increasingly disadvantaged in their healthcare access if mobile phones diffuse rapidly in their

701   environment. This assumed that health systems comprise actors with different degrees of

702   "responsiveness" to mobile phone use, and that increasing phone diffusion leads these responsive

703   providers to expect health-related phone use among the population. Fixed-effects linear probability

704   models with village-cluster robust standard errors using nationwide panel data from 2005 and 2012

705   lend support to this hypothesis: District-level mobile phone diffusion is negatively linked to rural

706   households' healthcare access, especially for poor households who tend to face more constraints, and

707   for private healthcare providers who tend to be more responsive to health-related mobile phone use.

708   Contrary to its common depiction, the process of digital inclusion delivers tools that intensify the

709   competition for scarce healthcare resource among deprived populations. These conditions indicate that

710   new phone-based technologies may help a broad part of the population to gain access to services, but

711   they are unlikely to include the most marginalised groups. Yet, acquiring a phone before everyone else

712   need not be advantageous either if the system cannot respond to its usage.

713   While the conclusion might look like we need more mobile phones for poor people in order to

714   keep them "competitive" and maintain or enhance their access to healthcare, there are two important

715   points that challenge this argument. First, the households who had not managed to acquire a mobile

716   phone are increasingly pressured to do so in order to maintain the same level of healthcare access at a

717   higher level of competition (note the resemblance to Lewis Carroll's Red Queen's race; Carroll,

718   1872:42), which is akin to a "tyranny" of technology adoption. This would not be the first argument

719   of its kind, as authors like Rich Ling argue that mobile technology has indeed now become so pervasive

720   in some domains of Western urban life that it is simply expected of everyone to use it so as to not

721   inconvenience others (Ling, 2012:178-179). In such situations, technology adoption stops being a free

722   choice. Second, more access to healthcare is not the same as access to better healthcare. The gradual

723   democratisation of health system utilisation can instead entail unnecessary treatment for minor

724   ailments, bypassing of referral systems put in place to ensure efficient health system operation, and

725   possible shifts away from less to more responsive healthcare providers with implications for the quality

726   of care received (Haenssgen, 2015a). I suggest that, in the struggle created during the process of digital

727   inclusion, persistently excluded parties require protection through conventional means such as efficient

728   public transport links, dependable and convenient clinic hours in local health centres, and guidelines

729   preventing healthcare providers to privilege patients accessing them through mobiles. Where mobile

730   phone use reduces the costs of public health service delivery, these savings can be put usefully towards

731   sustaining the healthcare access of more vulnerable parts of the population.

732   This study invites a number of questions for future research. Considering the nature of the

733   household panel, one of the more immediate questions is whether individual-level healthcare-seeking

734   panel data can shed further light on the implications and nuances of mobile phone diffusion in India.

735   Broader questions from a comparative perspective would investigate whether the experience of rural

736   India is generalizable, and, if not, what individual, social, infrastructural, technological, and health

737   system factors contribute to the mitigation and amplification of such effects. But struggles in the

738   process of digital inclusion might not be unique to healthcare, which raises the possibility that other

739   domains of digital development are affected as well. This might in particular be the case where mobile

740   phone use skews demand for scarce resources, for example employment, governmental services, or

741   time with social contacts. In addition to these mostly empirical considerations, further work to theorise

742   the social implications involved in the process of technology adoption is necessary to move away from

743   an idealised notions of inclusion. As Tim Unwin's book *ICT4D* opens with the lines "This book is

744   about how information and communication technologies (ICTs) can be used to help poor and

745   marginalised people and communities make a difference to their lives" (Unwin, 2009:1), perhaps we

746   should also start reflecting on how we can prevent ICTs from making poor and marginalised people's

747   lives worse.

748 **References**

749 Aker, J. C., Ksoll, C., & Lybbert, T. J. (2012). Can mobile phones improve learning? Evidence from

750   a field experiment in Niger. *American Economic Journal: Applied Economics, 4*(4), 94-120.

751   doi: 10.2307/23269743

752 Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *The Journal*

753   *of Economic Perspectives, 24*(3), 207-232. doi: 10.2307/20799163

754 Andersson, A., & Hatakka, M. (2013). *What are we doing? Theories used in ICT4D research*. Paper

755   presented at the 12th International Conference on Social Implications of Computers in

756   Developing Countries, 19-22 May, 2013, Ocho Rios, Jamaica.

757 Ayanso, A., Cho, D. I., & Lertwachara, K. (2013). Information and communications technology

758   development and the digital divide: a global and regional assessment. *Information Technology*

759   *for Development, 20*(1), 60-77. doi: 10.1080/02681102.2013.797378

760 Balabanova, D., & McKee, M. (2002). Access to health care in a system transition: the case of

761   Bulgaria. *The International Journal of Health Planning and Management, 17*(4), 377-395. doi:

762   10.1002/hpm.687

763 Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in northern mozambique.

764   *The Economic Journal, 116*(514), 869-902. doi: 10.1111/j.1468-0297.2006.01115.x

765 Barzilai-Nahon, K. (2006). Gaps and bits: conceptualizing measurements for digital divide/s. *The*

766   *Information Society, 22*(5), 269-278. doi: 10.1080/01972240600903953

767 Beals, A. R. (1976). Strategies of resort to curers in South Asia. In C. M. Leslie (Ed.), *Asian medical*

768   *systems: a comparative study* (pp. 184-200). Berkeley: University of California Press.

769 Bédoucha, G. (2002). The watch and the waterclock: technological choices/social choices. In P.

770   Lemonnier (Ed.), *Technological choices: transformation in material cultures since the*

771   *neolithic* (pp. 77-108). London: Routledge.

772 Besley, T., & Case, A. (1993). Modeling technology adoption in developing countries. *The American*

773   *Economic Review, 83*(2), 396-402.

774 Burrell, J. (2010). Evaluating shared access: social equality and the circulation of mobile phones in

775   rural Uganda. *Journal of Computer-Mediated Communication, 15*(2), 230-250. doi:

776   10.1111/j.1083-6101.2010.01518.x

777 Burrell, J., & Toyama, K. (2009). What constitutes good ICTD research? *Information Technologies &*

778   *International Development, 5*(3), 82-94.

779 Carroll, L. (1872). *Through the looking-glass, and what Alice found there. With fifty illustrations by*

780   *John Tenniel*. London: Macmillan and Co.

781 Chib, A. (2015). Research on the impact of the information society in the global south: an introduction

782   to SIRCA. In A. Chib, J. May & R. Barrantes (Eds.), *Impact of Information Society Research*

783   *in the Global South* (pp. 1-17): Springer Singapore.

784 Chipchase, J. (2006). How do you manage your contacts if you can't read or write? *interactions, 13*(6),

785   16-17. doi: 10.1145/1167948.1167966

786 Colson, A. C. (1971). The differential use of medical resources in developing countries. *Journal of*

787   *Health and Social Behavior, 12*(3), 226-237. doi: 10.2307/2948558

788 Desai, S., Dubey, A., Joshi, B. L., Sen, M., Sharif, A., & Vanneman, R. (2010a). *Human development*

789   *in India: challenges for a society in transition*. Oxford: Oxford University Press.

790 Desai, S., Vanneman, R., & National Council of Applied Economic Research. (2010b). *India Human*

791   *Development Survey (IHDS), 2005 [ICPSR22626-v8]*. Ann Arbour, MI: Inter-university

792   Consortium for Political and Social Research. Retrieved from

793   http://doi.org/10.3886/ICPSR36151.v3.

794 Desai, S., Vanneman, R., & National Council of Applied Economic Research. (2016). *India Human*

795   *Development Survey-II (IHDS-II), 2011-12 [ICPSR36151-v2]*. Ann Arbour, MI: Inter-

796   university Consortium for Political and Social Research. Retrieved from

797   http://doi.org/10.3886/ICPSR36151.v3.

798   Dewan, S., & Frederick, J. R. (2005). The digital divide: current and future research directions. *Journal*

799   *of the Association for Information Systems, 6*(12), 298-336.

800   Díaz Andrade, A., & Urquhart, C. (2012). Unveiling the modernity bias: a critical examination of the

801   politics of ICT4D. *Information Technology for Development, 18*(4), 281-292. doi:

802   10.1080/02681102.2011.643204

803   Dodson, L. L., Sterling, S. R., & Bennett, J. K. (2012). Considering failure: eight years of ITID

804   research. *Information Technologies & International Development, 9*(2, ICTD2012 Special

805   Issue), 19-34.

806   Donner, J. (2015). *After access: inclusion, development, and a more mobile Internet*. Cambridge, MA:

807   MIT Press.

808   Duncombe, R. (2012). *Understanding mobile phone impact on livelihoods in developing countries: a*

809   *new research framework* [Manchester Centre for Development Informatics Working Paper no.

810   48]. Manchester: Centre for Development Informatics, Institute for Development Policy and

811   Management.

812   Flor, A. (2015). Constructing theories of change for information society impact research. In A. Chib,

813   J. May & R. Barrantes (Eds.), *Impact of Information Society Research in the Global South* (pp.

814   45-62): Springer Singapore.

815   Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review*

816   *of Economics, 2*(1), 395-424. doi: doi:10.1146/annurev.economics.102308.124433

817   Fu, X., & Polzin, C. (2010). Sustainability of technology-intensive social innovation in India: the role

818   of absorptive capacity and complementary assets. In X. Fu & L. Soete (Eds.), *The rise of*

819   *technological power in the South* (pp. 320-340). Basingstoke: Palgrave Macmillan.

820   Gagliardone, I. (2015). 'Can you hear me?' Mobile-radio interactions and governance in Africa. *New*

821   *Media & Society,* (ahead of print), 1-16. doi: 10.1177/1461444815581148

822   Graham, M. (2011). Disintermediation, altered chains and altered geographies: the Internet in the Thai

823   silk industry. *Electronic Journal of Information Systems in Developing Countries, 45*(5), 1-25.

824   Graham, M., Hogan, B., Straumann, R. K., & Medhat, A. (2014). Uneven geographies of user-

825   generated information: patterns of increasing informational poverty. *Annals of the Association*

826   *of American Geographers, 104*(4), 746-764. doi: 10.1080/00045608.2014.910087

827   Greene, W. H. (2008). *Econometric analysis* (6th ed.). Upper Saddle River, N.J.: Pearson/Prentice

828   Hall.

829   Gudeman, S. (1992). Remodeling the house of economics: culture and innovation. *American*

830   *Ethnologist, 19*(1), 141-154. doi: 10.2307/644829

831   Gulliford, M., Figueroa-Munoz, J., Morgan, M., Hughes, D., Gibson, B., Beech, R.*, et al.* (2002). What

832   does 'access to health care' mean? *Journal of Health Services Research & Policy, 7*(3), 186-

833   188. doi: 10.1258/135581902760082517

834   Haenssgen, M. J. (2015a). *The effects of mobile phone use on healthcare-seeking trajectories in rural*

835   *India and China*. Paper presented at the 2015 International Health Conference, 25-27 June

836   2015, Oxford.

837   Haenssgen, M. J. (2015b). Exploring the mismatch between mobile phone adoption and use through

838   survey data from rural India and China. *Proceedings of the 2015 IEEE International*

839   *Symposium on Technology and Society (ISTAS)*, 1-15. doi: 10.1109/ISTAS.2015.7439402

840   Haenssgen, M. J. (2015c). *Mobile phone diffusion and rural healthcare access in India and China.*

841   (D.Phil. Thesis), University of Oxford, Oxford. Retrieved from

842   http://ora.ox.ac.uk/objects/uuid:3f48fc8b-5414-4851-926b-07a57eed6cfe

843   Haenssgen, M. J., & Ariana, P. (2015). *Does the rapid mobile phone diffusion in rural low- and middle-*

844   *income contexts undermine equitable access to healthcare? Survey evidence from rural India*

845   *and China*. Paper presented at the 13th Globelics International Conference, 23-25 September

846   2015, Havana.

847 Hahn, H. P., & Kibora, L. (2008). The domestication of the mobile phone: oral society and new ICT

848   in Burkina Faso. *The Journal of Modern African Studies, 46*(1), 87-109. doi:

849   doi:10.1017/S0022278X07003084

850 Hampshire, K., Porter, G., Owusu, S. A., Mariwah, S., Abane, A., Robson, E*., et al.* (2015). Informal

851   m-health: How are young people using mobile phones to bridge healthcare gaps in Sub-Saharan

852   Africa? *Social Science & Medicine, 142*, 90-99. doi:

853   http://dx.doi.org/10.1016/j.socscimed.2015.07.033

854 Hampshire, K. R., Porter, G., Owusu, S. A., Tanle, A., & Abane, A. (2011). Out of the reach of

855   children? Young people's health-seeking practices and agency in Africa's newly-emerging

856   therapeutic landscapes. *Social Science & Medicine, 73*(5), 702-710. doi:

857   10.1016/j.socscimed.2011.06.035

858 Heeks, R. (2008). ICT4D 2.0: the next phase of applying ICT for international development.

859   *Computer, 41*(6), 26-33. doi: 10.1109/MC.2008.192

860 Heeks, R. (2009). *The ICT4D 2.0 manifesto: Where next for ICTs and international development?*

861   [Development Informatics working paper series no. 42]. Manchester: Institute for

862   Development Policy and Management.

863 Heeks, R. (2014). *ICT4D 2016: new priorities for ICT4D policy, practice and WSIS in a post-2015*

864   *world* [Development Informatics working paper series no. 59]. Manchester: Institute for

865   Development Policy and Management.

866 Helsper, E. J. (2012). A corresponding fields model for the links between social and digital exclusion.

867   *Communication Theory, 22*(4), 403-426. doi: 10.1111/j.1468-2885.2012.01416.x

868 Horst, H. A. (2006). The blessings and burdens of communication: cell phones in Jamaican

869   transnational social fields. *Global Networks, 6*(2), 143-159. doi: 10.1111/j.1471-

870   0374.2006.00138.x

871 Horst, H. A., & Miller, D. (2006). *The cell phone: an anthropology of communication*. Oxford: Berg.

872   Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: evidence from Kenya's mobile money

873   revolution. *The American Economic Review, 104*(1), 183-223. doi: 10.1257/aer.104.1.183

874   Karnowski, V., von Pape, T., & Wirth, W. (2011). Overcoming the binary logic of adoption. In A.

875   Vishwanath & G. A. Barnett (Eds.), *The diffusion of innovations: a communication science*

876   *perspective* (pp. 57-76). New York: Peter Lang.

877   Katz, J. E. (2008). Introduction. In J. E. Katz (Ed.), *Handbook of mobile communication studies* (pp.

878   1-11). Cambridge, MA: MIT Press.

879   Kibadi, K., Boelaert, M., Kayinua, M., Minuku, J.-B., Muyembe-Tamfum, J.-J., Portaels, F.*, et al.*

880   (2009). Therapeutic itineraries of patients with ulcerated forms of Mycobacterium ulcerans

881   (Buruli ulcer) disease in a rural health zone in the Democratic Republic of Congo. *Tropical*

882   *Medicine & International Health, 14*(9), 1110-1116. doi: 10.1111/j.1365-3156.2009.02324.x

883   Kleine, D. (2013). *Technologies of choice? ICTs, development, and the capabilities approach.*

884   Cambridge, MA: MIT Press.

885   Kroeger, A. (1983). Anthropological and socio-medical health care research in developing countries.

886   *Social Science & Medicine, 17*(3), 147-161. doi: http://dx.doi.org/10.1016/0277-

887   9536(83)90248-4

888   Kurniawan, S. (2008). Older people and mobile phones: a multi-method investigation. *International*

889   *Journal of Human-Computer Studies, 66*(12), 889-901. doi:

890   http://dx.doi.org/10.1016/j.ijhcs.2008.03.002

891   Lieber, E., Li, L., Wu, Z., Rotheram-Borus, M. J., & Guan, J. (2006). HIV/STD stigmatization fears

892   as health-seeking barriers in China. *AIDS and Behavior, 10*(5), 463-471. doi: 10.1007/s10461-

893   005-9047-5

894   Ling, R. S. (2008). *New tech, new ties: how mobile communication is reshaping social cohesion.*

895   Cambridge, MA: MIT Press.

896   Ling, R. S. (2012). *Taken for grantedness: the embedding of mobile communication into society*.

897   Cambridge, MA: MIT Press.

898   May, J., & Diga, K. (2015). Progress towards resolving the measurement link between ICT and poverty

899   reduction. In A. Chib, J. May & R. Barrantes (Eds.), *Impact of Information Society Research*

900   *in the Global South* (pp. 83-104): Springer Singapore.

901   Mbiti, I. M., & Weil, D. N. (2011). *Mobile banking: the impact of M-PESA in Kenya* [NBER Working

902   Paper no. 17129]. Cambridge, MA: National Bureau of Economic Research.

903   Mechael, P. (2006). *Exploring health-related uses of mobile phones: an Egyptian case study*.

904   (Unpublished PhD thesis), London School of Hygiene and Tropical Medicine, London.

905   Mechael, P. (2008). Health services and mobiles: a case from Egypt. In J. E. Katz (Ed.), *Handbook of*

906   *mobile communication studies* (pp. 91-103). Cambridge, MA: MIT Press.

907   Meessen, B., Bigdeli, M., Chheng, K., Decoster, K., Ir, P., Men, C.*, et al.* (2011). Composition of

908   pluralistic health systems: how much can we learn from household surveys? An exploration in

909   Cambodia. *Health Policy and Planning, 26*(Suppl. 1), i30-i44. doi: 10.1093/heapol/czr026

910   Miller, D. (2010). *Stuff*. Cambridge: Polity Books.

911   Miritello, G., Moro, E., Lara, R., Martínez-López, R., Belchamber, J., Roberts, S. G. B.*, et al.* (2013).

912   Time as a limited resource: communication strategy in mobile phone networks. *Social*

913   *Networks, 35*(1), 89-95. doi: http://dx.doi.org/10.1016/j.socnet.2013.01.003

914   Moshabela, M., Pronyk, P., Williams, N., Schneider, H., & Lurie, M. (2011). Patterns and implications

915   of medical pluralism among HIV/AIDS patients in rural South Africa. *AIDS and Behavior,*

916   *15*(4), 842-852. doi: 10.1007/s10461-010-9747-3

917   Munn, N. D. (1992). The cultural anthropology of time: a critical essay. *Annual Review of*

918   *Anthropology, 21*, 93-123. doi: 10.2307/2155982

919   Nakahara, S., Saint, S., Sann, S., Ichikawa, M., Kimura, A., Eng, L*., et al.* (2010). Exploring referral
920   systems for injured patients in low-income countries: a case study from Cambodia. *Health*
921   *Policy and Planning, 25*(4), 319-327. doi: 10.1093/heapol/czp063

922   Napoli, P. M., & Obar, J. A. (2014). The emerging mobile Internet underclass: a critique of mobile
923   Internet access. *The Information Society, 30*(5), 323-334. doi: 10.1080/01972243.2014.944726

924   Nyamongo, I. K. (2002). Health care switching behaviour of malaria patients in a Kenyan rural
925   community. *Social Science & Medicine, 54*(3), 377-386. doi: http://dx.doi.org/10.1016/S0277-
926   9536(01)00036-3

927   Pearce, K. E. (2013). Phoning it in: theory in mobile media and communication in developing
928   countries. *Mobile Media & Communication, 1*(1), 76-82. doi: 10.1177/2050157912459182

929   Pedersen, M. A., & Bunkenborg, M. (2012). Roads that separate: sino-mongolian relations in the inner
930   Asian desert. *Mobilities, 7*(4), 555-569. doi: 10.1080/17450101.2012.718938

931   Peglidou, A. (2010). Therapeutic itineraries of 'depressed' women in Greece: power relationships and
932   agency in therapeutic pluralism. *Anthropology & Medicine, 17*(1), 41-57. doi:
933   10.1080/13648471003600404

934   Pitt, E., & Pusponegoro, A. (2005). Prehospital care in Indonesia. *Emergency Medicine Journal, 22*(2),
935   144-147. doi: 10.1136/emj.2003.007757

936   Qureshi, S. (2014). Overcoming technological determinism in understanding the digital divide: Where
937   do we go from here? *Information Technology for Development, 20*(3), 215-217. doi:
938   10.1080/02681102.2014.930981

939   Qureshi, S. (2015). Are we making a better world with information and communication technology
940   for development (ICT4D) research? Findings from the field and theory building. *Information*
941   *Technology for Development, 21*(4), 511-522. doi: 10.1080/02681102.2015.1080428

942   Rashid, A. T., & Elder, L. (2009). Mobile phones and development: an anaylsis of IDRC-supported
943   projects. *Electronic Journal of Information Systems in Developing Countries, 36*(2), 1-16.

944 Reisdorf, B. C., Axelsson, A.-S., & Söderholm, H. M. (2012). *Living offline: a qualitative study of*
945 *Internet non-use in Great Britain and Sweden*. Paper presented at the Association of Internet
946 Researchers Conference, 18-21 October 2012, Salford, UK.

947 Robinson, L., Cotten, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W*., et al.* (2015). Digital
948 inequalities and why they matter. *Information, Communication & Society, 18*(5), 569-582. doi:
949 10.1080/1369118X.2015.1012532

950 Roztocki, N., & Weistroffer, H. R. (2014). Information and communication technology in transition
951 economies: an assessment of research trends. *Information Technology for Development, 21*(3),
952 330-364. doi: 10.1080/02681102.2014.891498

953 Sæbø, Ø., & Furuholt, B. (2013). *The importance of unintended use: What are we not looking for in*
954 *ICT4D projects?* Paper presented at the 12th International Conference on Social Implications
955 of Computers in Developing Countries, 19-22 May, 2013, Ocho Rios, Jamaica.

956 Saramäki, J., Leicht, E. A., López, E., Roberts, S. G. B., Reed-Tsochas, F., & Dunbar, R. I. M. (2014).
957 Persistence of social signatures in human communication. *Proceedings of the National*
958 *Academy of Sciences, 111*(3), 942-947. doi: 10.1073/pnas.1308540110

959 Schroeder, R. (2010). Mobile phones and the inexorable advance of multimodal connectedness. *New*
960 *Media & Society, 12*(1), 75-90. doi: 10.1177/1461444809355114

961 Schroeder, R. (2015). A Weberian analysis of global digital divides. *International Journal of*
962 *Communication, 9*, 2819–2837.

963 Seddon, N. (2007). *Quite like heaven? Options for the NHS in a consumer age*. Bury St Edmunds: St
964 Edmundsbury Press.

965 Sen, A. (1999). Health in development. *Bulletin of the World Health Organization, 77*(8), 619-623.

966 Shaikh, B. T., Haran, D., & Hatcher, J. (2008). Where do they go, whom do they consult, and why?
967 Health-seeking behaviors in the northern areas of Pakistan. *Qualitative Health Research, 18*(6),
968 747-755. doi: 10.1177/1049732308317220

969 Shaikh, B. T., & Hatcher, J. (2005). Health seeking behaviour and health service utilization in Pakistan:

970   challenging the policy makers. *Journal of Public Health, 27*(1), 49-54. doi:

971   10.1093/pubmed/fdh207

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

973 Steenson, M. W., & Donner, J. (2009). Beyond the personal and private: modes of mobile phone

974   sharing in urban India. In R. Ling & S. W. Campbell (Eds.), *The reconstruction of space and*

975   *time: mobile communication practices* (pp. 231-250). New Brunswick, NJ: Transaction

976   Publishers.

977 Stewart, F. (1978). *Technology and underdevelopment* (2nd ed ed.). London: Macmillan.

978 Storla, D. G., Yimer, S., & Bjune, G. (2008). A systematic review of delay in the diagnosis and

979   treatment of tuberculosis. *BMC Public Health, 8*(15).

980 Stump, R. L., Wen Gong, & Zhan Li. (2008). Exploring the digital divide in mobile-phone adoption

981   levels across countries: Do population socioeconomic traits operate in the same manner as their

982   individual-level demographic counterparts? *Journal of Macromarketing, 28*(4), 397-412. doi:

983   10.1177/0276146708325386

984 Sudhinaraset, M., Ingram, M., Lofthouse, H. K., & Montagu, D. (2013). What is the role of informal

985   healthcare providers in developing countries? A systematic review. *PLoS ONE, 8*(2), e54978.

986   doi: 10.1371/journal.pone.0054978

987 Thompson, E. P. (1967). Time, work-discipline, and industrial capitalism. *Past & Present*(38), 56-97.

988   doi: 10.2307/649749

989 UNDP. (2014). *Human development report 2014: sustaining human progress: reducing vulnerabilities*

990   *and building resilience*. New York, NY: United Nations Development Programme.

991 Unwin, T. (2009). Introduction. In T. Unwin (Ed.), *ICT4D: information and communication*

992   *technology for development* (pp. 1-6). Cambridge: Cambridge University Press.

993   van Dijk, J. (2005). *The deepening divide: inequality in the information society*. Thousand Oaks, CA:

994   Sage.

995   van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics, 34*(4–

996   5), 221-235. doi: http://dx.doi.org/10.1016/j.poetic.2006.05.004

997   van Egeren, L., & Fabrega, H. (1976). Behavioral science and medical education: A biobehavioral

998   perspective. *Social Science & Medicine, 10*(11–12), 535-539. doi:

999   http://dx.doi.org/10.1016/0037-7856(76)90021-4

1000   Walsham, G. (2013). Development informatics in a changing world: reflections from ICTD2010/2012.

1001   *Information Technologies & International Development, 9*(1), 49-54.

1002   Ward, H., Mertens, T. E., & Thomas, C. (1997). Health seeking behaviour and the control of sexually

1003   transmitted disease. *Health Policy and Planning, 12*(1), 19-28.

1004   WHO. (2007). *Strengthening health systems to improve health outcomes: WHO's framework for*

1005   *action*. Geneva: World Health Organization.

1006   WHO. (2010). *Strengthening care for the injured: success stories and lessons learned from around*

1007   *the world*. Geneva: World Health Organization.

1008   Wyche, S. (2015). *Exploring mobile phone and social media use in a Nairobi slum: a case for*

1009   *alternative approaches to design in ICTD*. Paper presented at the Proceedings of the Seventh

1010   International Conference on Information and Communication Technologies and Development,

1011   Singapore. http://delivery.acm.org/10.1145/2740000/2738019/a12-

1012   wyche.pdf?ip=129.67.117.236&id=2738019&acc=ACTIVE%20SERVICE&key=BF07A2E

1013   E685417C5%2EF2FAECDC86A918EB%2E4D4702B0C3E38B35%2E4D4702B0C3E38B3

1014   5&CFID=529628244&CFTOKEN=96446614&__acm__=1437484468_d40f28b620a3a74c8

1015   1e11d749c1f5e95

1016   Ziefle, M., & Bay, S. (2005). How older adults meet complexity: aging effects on the usability of

1017   different mobile phones. *Behaviour & Information Technology, 24*(5), 375-389. doi:

1018   10.1080/0144929042000320009

1019   **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.