Information as an Environmental Policy Instrument: Examining Household Response to Arsenic in Tube-Well Water in Araihazar, Bangladesh

by

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Dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in the
Department of Environment in the
Graduate School of Duke University

2011

ABSTRACT

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Abstract

This dissertation examines the potential of information-provision in motivating behavior that reduces human exposure to arsenic in drinking-water in Bangladesh. In chapter 2, the longer-term effects of the countrywide arsenic-testing and information-program are examined by tracking tube-well switching behavior of households over a five-year period. Chapter 3 focuses on the effects of arsenic information communication formats on tube-well switching behavior, by employing a randomized field experiment. In chapter 4, an instrumental variables approach is used to understand whether a household's decision to switch sources is affected by its proximate neighbors' decisions to switch sources. To answer these questions, primary data was collected by the researchers through field-work in Bangladesh. The results suggest that arsenic-testing and information-provision programs produce persistent behavioral changes that reduce exposure to arsenic, with their impact increasing over time. Comparing the impacts of risk-communication formats, we find that quantitative formats do not significantly increase source-switching behavior, in comparison to that generated by qualitative formats. Lastly, despite econometric identification issues, our data suggest that households gather information about source-switching by observing the actions of their neighbors. In sum, the results presented in this dissertation suggest that the provision of information to rural households can motivate health-improving behavior that reduces

households' exposure to arsenic in Bangladesh. This dissertation contributes to the use of information disclosure as a policy instrument to reduce exposure to environmental contaminants.

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I dedicate this dissertation to my parents.

1. Introduction

This dissertation contributes to the use of information disclosure as a policy instrument to reduce exposure to environmental contaminants. In this dissertation, I examine the problem of arsenic in groundwater in Bangladesh to understand whether providing information on arsenic content of tube-wells helps households choose safer wells as water sources.

Arsenic in ground water is a global environmental health problem. Large populations are exposed to elevated levels of arsenic in many countries in Asia—six million in China; five million in India; ten million in Vietnam; three million in Cambodia(World Bank 2005). In Bangladesh, consumption of groundwater began in the 1970s, when the Department of Public Health and Engineering (DPHE) began facilitating the installation of public tube-wells across Bangladesh. This shift to groundwater was primarily undertaken to reduce the consumption of bacterially-contaminated surface water, which was the primary factor responsible for high rates of infant mortality. Shallow tube-wells are inexpensive to dig, are a convenient water source, and accord women privacy; therefore private wells installed in courtyards of homes began proliferating across the country. Presently, groundwater pumped through private tube-wells is the primary water source for 90% of the population,

At the time the government program encouraging the installation of tube wells was implemented, it was not known that the ground water in Bangladesh is heavily contaminated with naturally occurring arsenic. Arsenic is detrimental to human health and is linked to cancers, cardiovascular diseases, metabolic disorders, cognitive delays and all cause-mortality. While the effects of arsenic-exposure are cumulative, it is not well understood whether and, if so, how quickly, the health risks dissipate upon cessation of exposure. This poses a major challenge for water security and human health.

With the discovery of arsenic in Bangladesh and other Asian countries, testing efforts to determine the contamination problem in Bangladesh were initially spearheaded by the British Geological Survey (BGS WC/00/19). Between 1999 and 2005, the World Bank funded a program called the Bangladesh Arsenic Mitigation Water Supply Project (BAMWSP), under which five million tube-wells were tested for arsenic. Using a cutoff value of 50 parts per billion(ppb), safe/ unsafe sources were identified by painting the spouts of tube-wells green/red. This testing program estimated that one-third of Bangladesh's population is exposed to arsenic above 50 ppb, while almost half the population is exposed to arsenic above 10 ppb. However, there is great heterogeneity in the occurrence of arsenic even within small areas like villages; therefore, the dominant policy response has been to provide well arsenic information by painting wells and

motivating households to discontinue drinking from red wells and switch to consuming water from green wells.

Information provision is increasingly being used as a policy instrument, often complementing traditional methods of regulation. Information programs can be used to motivate producers and consumers to either take actions private actions or push for better regulation; they can also be used to better inform the state and enable new or better regulation.

Information provision has been used to reduce asymmetries in information, in order to help economic agents make choices that improve social welfare (Akerlof, 1970). The field of environmental economics has traditionally focused on reducing pollution and improving social welfare by using monetary instruments like taxes and permits (Pigou 1920; Dales 1968; Montgomery 1972; Tietenberg 1985; Hahn & Stavins 1992; Keohane et al. 1999). Of late, information disclosure is also being used to regulate polluting firms in developed countries. These disclosures of pollutants mandated by the Toxic Release Inventory Program have led to dirty firms' market values being adversely affected, thus giving firms incentives to change their polluting behavior and uptake abatement activities (Hamilton 1995; Wolf 1996; Konar and Cohen 1997; Khanna et al.

1998; Karkkainen 2001; King and Lenox 2001; Bennear 2007). [1] Disclosure programs like eco-labeling have been used to promote consumers to buy products that are environmentally friendly, thus creating incentives for firms to produce such products (Blend & van Ravenswaay 1999; Gallastegui 2002; Banerjee & Soloman 2003; Sammer & Wüstenhagen 2006).

Information campaigns are increasingly being used in the field of public health to promote behaviors like safe sex (Alstead et al. 1999), regular health-monitoring and screening (Fender et al. 1999; Black et al. 2002), and smoking cessation (Farrelly et al. 2000; Siegel & Beiner 2000). Nutrition labels are being used to enable costumers to make dietary choices that are appropriate for them (Kim et. al 2000; Mathios 2000; Balasubramanian and Cole 2002; Neuhouser et. al 1999; Variyam and Cawley 2006; Harnack and French 2008; Downs et. al 2009; Wisdom et. al 2010). In developing countries, provision of information on various health risks has been facilitated by the state to motivate practices in the fields of vaccination and in water, sanitation and hygiene that reduce exposure to health-risks, many of which are leading causes of heavy disease burden in developing countries((Siriwardena et al. 2002; Sircar et al. 1987; Stanton & Clements 1987; Fewtrell et al. 2005; Pattanayak et al. 2006; Madajewicz et al. 2007; Jalan & Somanathan 2008). The results from this literature suggest that

[1] Recent work by Powers et al. 2008 suggests that such a disclosure program in India has also led to dirty firms reducing their pollution load.

information provision motivates better health practices, but its effects vary across education and income cohorts. Additionally, groups that are at the greatest risk may not be the greatest beneficiaries of such programs (Shimshak et al. 2007).

Related literature has focused on the methods of risk communication. Prospect theory in the field of psychology suggests that the people are sensitive to framing effects and thresholds (Kahneman & Tversky 1979), thereby creating a role for communication methods to influence desirable behavior. The literature on the use of qualitative vs. quantitative messages (Smith et al. 1988; Smith et al. 1995) suggests that thresholds and prescriptive messages motivate action better than complex quantitative and suggestive messages, and create goals that policy-makers can work towards (Russel & Gruber 1987). However, thresholds lead to discontinuity in responses to small changes of risk, and create a world of "safe" and "unsafe" (Smith et al. 1990).

Another body of literature examines the flows of information between agents to examine whether the latter receive information about benefits and costs of potential actions from their peers. Initially focusing on the spread of new agricultural technology (O'Mara 1971; Foster and Rosenzweig 1995; Bikhchandani et al. 1998; Conley and Udry 2001; Munshi 2004; Conley and Udry 2010), this literature now also considers whether health-related attitudes and practices are influenced by peers (Behrman et al. 2001; Munshi and Myaux 2006; Miguel and Kremer 2007; Oster and Thornton 2008). This

literature finds that learning from peers is likely to be greater amongst homogeneous groups than heterogeneous ones.

This dissertation combines and builds on all three of the previously-mentioned strands of literature by examining the pathways through which households in rural Bangladesh respond to information about tube-well arsenic. Chapter 2 examines the long-term impact of the countrywide testing and information campaign implemented in Bangladesh. The results suggest that the information and testing program in Bangladesh produced persistent exposure-reducing behavior which spread through households over a five-year period.[2] Chapter 3 tests whether the format of communicating arsenic-exposure risks matters differentially motivates the adoption of exposure-reducing behavior. The results suggest that better but complex risk information enhanced exposure-reducing behavior only for a households exposed to moderate levels of arsenic in that group and did not make a significant difference for the majority of the study group, in comparison to a simple prescriptive information format that conveyed thresholds.[3] Chapter 4 considers whether households are more likely to undertake

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[2] This chapter is a paper with H.B. Soumya, A. Pfaff, L. Bennear, A. Tarozzi, A. Schoenfeld, K.M. Ahmed and A. van Geen. The survey for collecting data was designed collaboratively by Pfaff, Bennear, Tarozzi and me. I was in charge of implementing the survey in the field; hiring, training, supervising and leading a field team to administer the survey and collect data in Bangladesh. I also conducted data cleaning and data analysis. A. Pfaff and I are co-lead authors on the paper. L. Bennear, A. Tarozzi, A. Schoenfeld, K.M. Ahmed and A. van Geen are co-authors.

[3] Chapter 3 is a paper with L. Bennear, A. Tarozzi, A. Pfaff, H.B. Soumya, A. Schoenfeld, K.M. Ahmed and A. van Geen. The baseline and follow-up surveys for collecting data were designed collaboratively by

exposure-reducing behavior if their geographically-proximate neighbors undertake such behaviors. While the data are suggestive of households adopting exposure-reducing behavior later because of interactions with friends, estimating a causal effect of the neighbors' behavior on a household's behavior remains challenging.[4]

The results in this dissertation suggest that testing campaigns can be used to encourage behaviors that promote health. Providing simple information about the relative safety of water source-options is an effective tool to motivate households to consume water from safer sources. Such information can be used a complement to the efforts of the National Policy for Arsenic Mitigation in Bangladesh that aims to promote piped water, using surface water as a primary water source (DPHE 2004). While the push for piped-drinking water in Bangladesh is certainly desirable, it is likely be to challenging to lay pipes in a country where 90% of the population draws groundwater by installing a shallow private tube-well in the courtyard of its dwelling. Surface water in Bangladesh continues to be heavily contaminated with microbial contaminants and

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Bennear, Tarozzi, Pfaff and me. I was in charge of implementing both surveys in the field; hiring, training, supervising and leading a field team to administer the surveys and collect data in Bangladesh. I have assisted with data cleaning and data analysis for this paper.

[4] Chapter 4: the data comes from chapter 2 and 3. The surveys for collecting these data sets were designed collaboratively by Bennear, Tarozzi, Pfaff and me. I was in charge of implementing these surveys in the field and collecting data in Bangladesh. I have conducted analysis of the data, and authored the chapter.

pollutants from domestic and industrial waste, and will require extensive purification. Rural Bangladesh has yet to experience piped water seven years after the formulation of the National Arsenic Mitigation Policy. Tube-wells remain the most popular source of water due to their convenience and privacy, and are likely to continue to be the dominant source of water (Caldwell et al. 2005). It is estimated currently that about one-third of wells in Bangladesh are still untested, due to the continued installation of tube-wells (BRAC 2008). Given that the effects of arsenic are cumulative, the Department of Public Health and Engineering (Government of Bangladesh) is likely to lose a window of opportunity to reduce exposure to arsenic if it does not consider the potential of information-provision in reducing exposure to arsenic. In sum, providing access to potable water in Bangladesh is going to be challenging. The need of the hour is to recognize the potential of all options that increase access to potable water and use them towards achieving water security.

2. Risk Information's Increasing Gains: Evidence from Arsenic in Bangladesh

2.1 Introduction

Information and public-health campaigns are increasingly being used to motivate desirable behaviors and influence knowledge and choices. In developing countries, such campaigns are being used not only to enable individuals to make informed decisions, but also to regulate human exposure to environmental and health risks by sharing the burden of regulation between the state and private decision-makers. These nations are unable to provide sufficient quantities of environmental amenities (like potable water and clean air) and often lack institutional and technological capacity to ensure adherence to environmental and health standards, and to respond to mass outbreaks of diseases. If risk-information provision is facilitated, individuals may be motivated to incur privately borne costs and take actions or change behaviors that avoid damages to their health. This underscores the importance of understanding whether information and public-health campaigns do indeed motivate behaviors that reduce exposure to health-damaging environmental risks. Existing evaluations of campaigns providing information to individuals on health risks (for example, Duflo et al. 2006, Pattanayak et al. 2006; Madajewicz et al. 2007; Jalan & Somanathan, 2008; Dupas 2010), which have typically been conducted in the short term, have demonstrated that information alone can motivate changes in behavior that reduce or avoid exposure to

risks, and are therefore potentially health-improving. However, not much is known about whether these desirable behavior changes are persistent over time. Additionally, whether these behavior changes diffuse in a population over the longer term is also not well understood. We provide evidence on both effects—persistence and diffusion of behavioral responses—by considering the case of arsenic in groundwater in Bangladesh.

Exposure to arsenic in groundwater is a significant health risk for tens of millions of people in South and South-East Asia (World Bank 2005). Almost 50% of the entire population of Bangladesh in 2000 was consuming groundwater with arsenic concentrations above the World Health Organization standard of 10 parts per billion (ppb), and almost one-third above 50 ppb (the Bangladesh standard for arsenic). Such exposure has been linked to increased risk of various cancers, cardiovascular disease, toxic effects on the liver, kidney, skin, and lung, neurological impairments and delays in the cognitive development of children (Chen et al. 1986; Wu et al. 1989; Tsuda et al. 1995; Tseng et al. 1996; Hopenhayn-Rich et al. 1998; Lewis et al. 1999; Ferreccio et al. 2000; Morales et al. 2000; Calderon et al. 2001; Tseng et al. 2002; Haque et al. 2003; Tsai et al. 2003; Wasserman et al. 2004, 2007; Yang et al. 2008), with latency periods of 5 to 15 years for early health effects and 20 or more for cancers(Guha-Mazumder et al. 1998; Milton & Rahman 1999; Smith et al. 2000). Field testing conducted by the Department of

Public Health and Engineering (DPHE) and the UNICEF, using arsenic field kits, indicate that about 60% of wells in Bangladesh contain arsenic above the country standard (BRAC 2000). In Araihazar, where 40% -60% of tubewells contain arsenic above 50 ppb (van Geen et al. 2003), it has been estimated that 20% of all-cause mortality and 25% of chronic disease mortality could be linked to elevated well arsenic (Argos et al. 2010).

Until the 1970s, the primary source of drinking water in Bangladesh was surface water. Groundwater was promoted to help reduce the incidence of water-borne diseases, which was the leading cause of high rates of infant mortality. The initial installation of wells was assisted by the government, however private installation of wells soon dominated, due to the low costs of installation, the convenience of having a nearby water source and privacy associated with using one's own well (Caldwell et al. 2003). By 1990, private well water was the primary drinking water source for over 90% of the population and over 95% of the rural population (WDR 2000/2001; Caldwell et al. 2003).

While various risks to health from consuming bacterially-contaminated surface water were well known, it was not known that the groundwater was contaminated with naturally-occurring arsenic. The detection of arsenic-related skin symptoms in India in the mid 1980s led to groundwater testing and the discovery of significant arsenic in

groundwater in West Bengal, India and in Bangladesh (Chakraborty & Saha 1987). The World-Bank-sponsored country-wide Bangladesh Arsenic Mitigation Water Supply Program (BAMWSP) tested about 5 million tube-wells between 1999 and 2005 free of charge, painting wells red to indicate arsenic above 50 ppb ("unsafe") and green for below 50 ppb ("safe"). Households were exhorted to drink only from green wells and to share safe wells with others. Arsenic level, determined by local geology, can vary greatly even within a village (van Geen et al. 2003; van Geen et al. 2006), making well testing and labeling a viable strategy for encouraging switches to safe wells.

In 2004, the National Policy for Arsenic Mitigation was formulated and it focuses on the promotion of piped water, paying little attention to well testing and labeling. This policy lists surface water as sources of piped-water supply (World Bank 2004), which will require considerable treatment for organic and inorganic contaminants before it is usable. Till date, piped drinking water has not reached very far into rural areas, and these populations continue to depend on groundwater pumped through private tubewells. The National Policy also raises doubt about the size and even existence of net welfare gain from well switching, given the inconvenience of traveling from one's well and of sharing a well with a neighbor (World Bank 2004).

Contrary to those doubts, it has now been documented that voluntary well switching does occur following testing and labeling. This switching from unsafe to safe

wells has reduced exposure to arsenic, as demonstrated by reductions in urinary arsenic-levels (Chen et al. 2007). A number of short-term studies of responses within 6months to 2 years of well testing in Bangladesh show that a third to a half of households switched upon learning their source was unsafe (Chen et al. 2007; Madajewicz et al. 2007; Opar et al. 2006)[1], despite having to walk further and thus incur costs of effort and time and perhaps income (Madajewicz et al. 2007). In fact, the reductions in exposures brought about by well testing, labeling and switching are larger than those achieved through any other arsenic-health intervention (Ahmed et al. 2007).

Nonetheless, switching rates could fall to zero in the longer term if households switch from unsafe to safe sources in the short term but then return to their unsafe sources over time. There are two distinct reasons this might occur. First, supply of safe wells could fall if safe-well owners discontinue providing access to their wells due to the wear-and-tear of the hand pump from more users, or due to loss of their privacy (Hanchett et al. 2002). Second, the demand for safe wells could fall if health concerns following unsafe tests fade with time, or the cost of using a neighbor's well—increase in walking time to fetch water, loss of convenience and privacy or perceived social

[1]These studies were conducted in academic research sites, where households have benefitted from continuous exposure to the presence of researchers and public health workers, as well as continued testing of new tube-wells. While these studies have provided important information about household behavior and health outcomes of such behavior, the switching rates and behavior observed among these households are unlikely to be representative of those generated by BAMWSP-testing, which was a simple program that involved one-shot testing and exposure to public-health workers.

obligation—increase over time. In sum, households who have switched wells might switch back to their unsafe source over time due to these supply and demand constraints. [2] On the other hand, if gathering and processing of information leading to switching takes time, more households may switch in the longer term than in the short term. Meanwhile, it is estimated that at least one-third of all tube-wells in Bangladesh have not been tested for arsenic due to ongoing installations of many new private wells (BRAC 2008). This situation emphasizes the importance of understanding the longer-term impacts of testing, as the national government and external donors consider whether to allocate more resources to testing.

We provide a novel evaluation of longer-term impacts of BAMWSP well testing on households' well-switching choices. Households in Araihazar received arsenic test-results for their private tubewells from BAMWSP by 2003 and we track these households to observe their switching decisions over two time periods. Specifically, we examine the 2005-08 switching decisions of households whose well switching behavior during 2003-05 was documented in Schoenfeld (2005). This lets us gauge if switching from unsafe sources is temporary or instead, well-switching is higher in the longer term than in the short term. To our knowledge, this is the first effort to document switching

[2] These well-switching constraints are likely to be stronger in areas that have not experienced continuous testing and research efforts—the majority of the country's population.

over time and also one of few studies that examines the longer-term impacts of public-health campaigns.

We find that early-period well-switching is overwhelmingly persistent with no household that switched in 2003-05 returning to its unsafe-tested source during 2005-08. We also find that switching rates in the longer term almost doubled that observed in the short term. Over 5 years, 42% of households whose wells had been tested unsafe switched sources as compared to 24% who has switched within two years. We also find that 78% of households tested unsafe and 80% of households tested safe continue to correctly perceive the safety of their BAMWSP-tested well 5 years after it was tested, despite paint having faded. These results indicate that one-shot BAMWSP testing and information provision has produced persistent changes in water-source choices, and this source-switching behavior has spread within this population over 5 years.

The chapter proceeds as follows: Section 1.2 describes the data. Methods and results can be found in Section 1.3 and we offer some policy implications in Section 1.4.

2.2 Data

The data used in this study originates from the sample surveyed by Schoenfeld (2005) between 2003 and 2005. Schoenfeld's study was carried out across 62 villages in Araihazar in areas covered by the BAMWSP testing campaign in 2003. From a database of BAMWSP well-tests, 8 villages were chosen with a balanced distribution of safe and

unsafe wells (50/50), and 8 villages were chosen for having a particularly high proportion (80–100 %) of unsafe wells. An additional 46 villages were later added with medium to high proportions of unsafe wells (Figure 1). In each village, the team approached owners of all tube-wells that they could find and administered a short survey to the female responsible for making decisions about water sources—usually the wife of the well-owner. Surveyors also recorded the Global Positioning System (GPS) coordinates of the tube-well and the color of the paint on the tubewell spout. The respondents were also asked to recall the result of their well test. In all, 3056 households were surveyed.

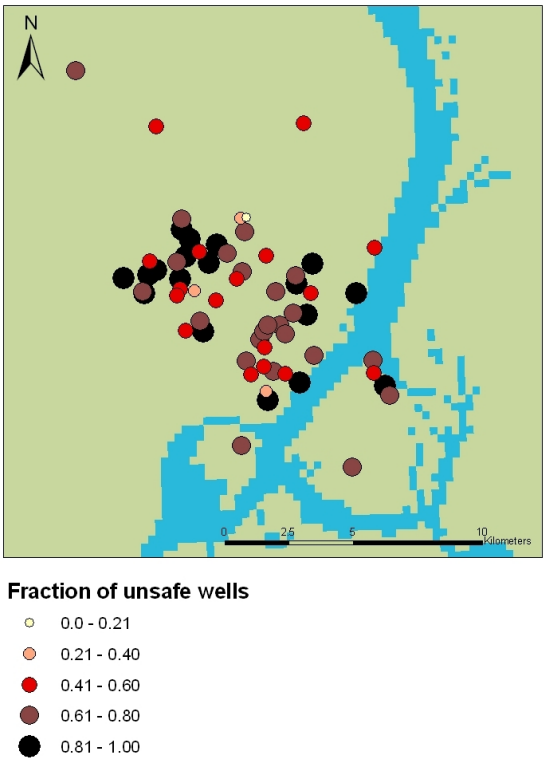

Figure 1: Fraction of unsafe wells in study area(by village)

Between January and April 2008, we conducted a follow-up survey with a subset of these households. Our survey instruments were pre-tested in 2 of the 62 villages. Data from these villages (52 households) are not used for our analysis. An additional village could not be visited due to time constraints, losing 3 further households. In each of the remaining 59 villages, a random number was generated for each tube-well in the database. Interviews were conducted with owners of tube-wells in ascending order of random numbers. This provided a random sample of 1557 households. Enumerators could remain in each village only for a limited number of days; therefore the proportion

of households surveyed within a village would vary by village size, implying that households from smaller villages were more likely to be included in our sample. Because we only interviewed a sample of households in each village, we use sampling weights throughout our analyses to account for the different probability of inclusion in our sample.

2.2.1 Summary statistics

Our 2008 survey was answered by the female who is the primary person responsible for choices about water sources in all interviews (Table 1). The population in our sample is not very literate and is relatively poor. About 48% of respondents could read and write *Bangla,* and around 62% of members in a household had completed primary education. Mean monthly household income and household expenditure were relatively low, at 8674 and 6234 Takas respectively, or US$299 and US$215 [3] , and only 13% of households lived in pukka (or brick) dwellings. However, this population has access to sanitation services, with 85% of households using a sanitary latrine. Self-reported symptoms of arsenic-related illnesses are also low; only 10% of households had at least one member with symptoms, and only 6% reported knowing neighbors with such illness. Interactions with neighbors about arsenic is not uncommon; 28% of

[3] Using a purchasing power parity rate of 29 Takas to US$1 in 2008(source: United Nations Statistics Division http://unstats.un.org/unsd/mdg/SeriesDetail.aspx?srid=699)

households reported that they had discussed risks of arsenic with neighbors (discussions with friends and relatives outside the village were less frequent). On average, a households was able to name other 1.6 households in their villages whose wells had also been tested for arsenic. Arsenic-safe sources are reasonable close; a household was about 34 meters away from the closest arsenic-safe well. This distance is the Euclidian distance between the household's BAMWSP-tested well and the closest well tested safe by BAMWSP, and is calculated by us, using GIS.

2.3 Methods and Results

We evaluate the persistence and diffusion of switching decisions using self-reported behavior collected from the respondent, who was asked to recall the household's switching decision in 2003-05 and in 2005-08. This allows us to indentify households as never switchers (67%), early switchers (14%), late switchers (15%) and both-period switchers (4%).[4] We also asked the respondent her perception about the arsenic-safety of the household's BAMWSP-tested well. In 2005, Schoenfeld's team had collected data on the color of the paint applied on the tubewell by BAMWSP, and the perception of the female decision-maker about the arsenic-safety of the BAMWSP-tested

[4] We also constructed the four types of switchers using Schoenfeld's 2005 data of switching behavior in 2003-05 and our 2008 data of switching behavior in 2005-08, and find never switchers (66%), early switchers (15%), late switchers (14%) and both period switchers (5%). We find no difference between these behavior patterns and the patterns calculated using our data. So we proceed using our data, to minimize authorship dilemmas.

well. These data allows us to check whether households' perceptions about their BAMWSP-tested well in two time periods lines up with the arsenic test-result provided by BAMWSP. We are thus able to distinguish between households that continue to perceive the safety of their well correctly through 2008, and those whose perceptions change. We use this information on test-results, perceptions and switching choices in two time periods to break down households into sixteen categories (Table 2) to understand longer-term switching behavior.

2.3.1 Switching behavior is persistent

Well-switching was frequently chosen by households whose wells had been painted red and whose owners consistently perceived that well as unsafe through 2008 (803 households in Table 2, column 1). Specifically, 42% of these households (19% early switchers, 18% late-switchers and 5% both-period switchers) switched sources at least once at some point during 2003-08 (Figure 2A). This aggregate result reinforces previous findings that contrary to initial doubts, households are willing to give up the convenience of their own well if they perceive health risks from that well. Dividing well-switching into two time-periods—2003-05 and 2005-08—allows us to examine the persistence of switching. During the first period of observed choices (2003-05), 24% of these households switched away from their unsafe wells—19% early switchers and 5%

both-switchers (Figure 2A). Therefore, 80% of early switchers (19/24) switched away from their unsafe well and stayed at that new source.

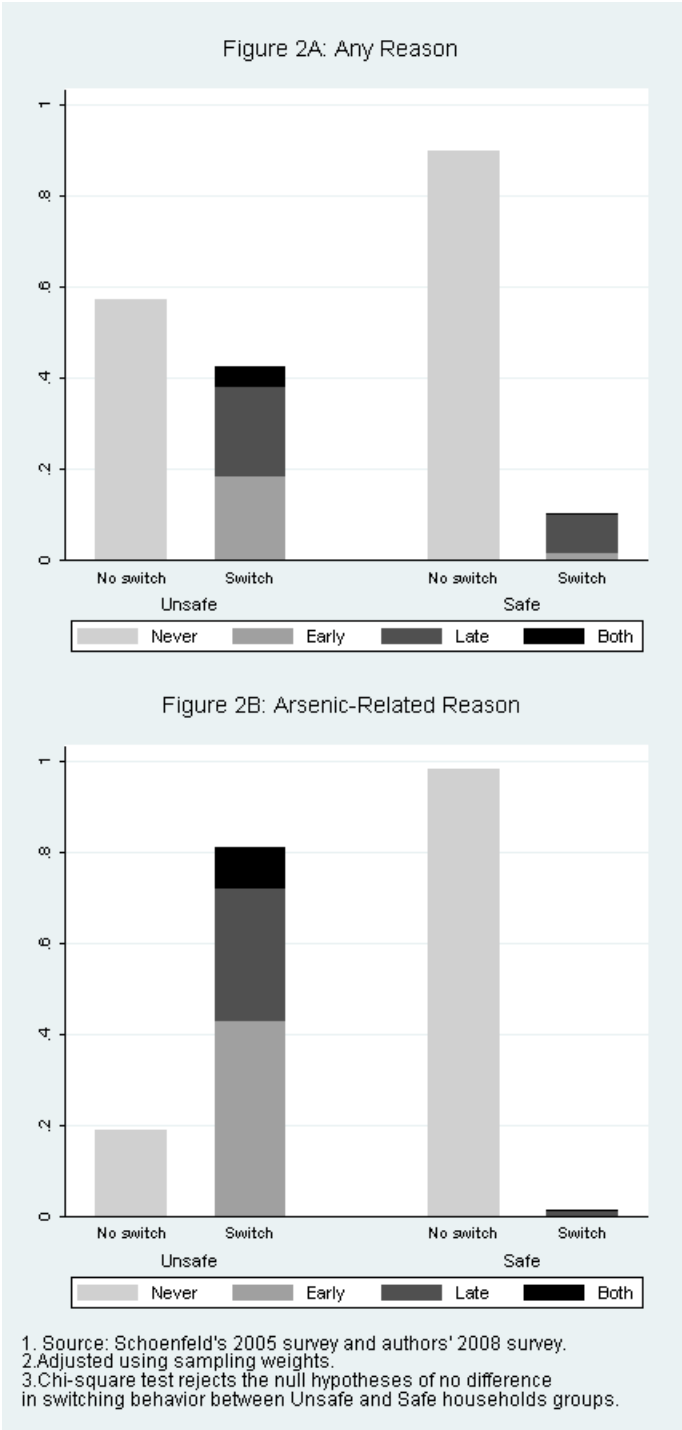

Figure 2: Switching behavior—households with correct status perception.

We asked households that had switched twice to indicate whether they had switched away from their unsafe well during 2003-05 only to switch back to their unsafe well later, in 2005-08. No such household had moved back to its 2003 unsafe well. Over half of these households reported that they had switched drinking sources during 2003-05 because their primary well had been found to be arsenic-unsafe. When these households switched again in 2005-08, about one third reported that they had moved to a closer well (presumably to reduce walking), a quarter said they had moved from a neighbor's well to one that they had installed (presumably for privacy and convenience) and another quarter reported that they had switched to a second safe well. Our evidence indicates that switching from unsafe sources is a persistent behavior, and households are unlikely to undo their decisions and return to an unsafe well they had discontinued using.

2.3.2 Switching rates increase over the longer-term

Among the 803 households above (whose wells had been painted red by BAMWSP and whose owners continued to consistently perceive that well as unsafe through 2008) 18% are late switchers—they did not switch sources in 2003-05, but did switch in 2005-08 (Figure 2A). Such late switchers raise testing's longer-term impact above short-term impact—nearly doubling the fraction of households switching from 24%in the short term to 42% in the longer term. Despite no new well testing being

conducted after 2003, it appears that over time the perceived net benefit of switching rose for a significant set of households.

Yet factors other than arsenic may have prompted some of the observed well switching. For instance, the well may cease to function. In order to get a clearer picture of the differences in switching rates due to arsenic, in Figure 2B we examine the subsample of households in Figure 2A who mention concerns about arsenic, or lack thereof, as a reason for switching or not switching. For this subsample (not a representative group) we see that differences in switching rates between households tested safe (80%) and those tested unsafe (1%) is even more pronounced. Thus not only are early switches persistent, we also find evidence that risk communication spurs new actions to lower exposures 2-5 years after the well tests and risk communication.

2.3.3 Arsenic tests drive switching behavior

We calculate switching rates for households whose wells were tested safe by BAMWSP and who consistently perceived the arsenic-safety of their well as "safe" through 2008 (419 households in Table 2, column 18) in order to compare their switching behavior to households whose wells were tested unsafe and who consistently perceived their BAMWSP-tested well as unsafe through 2008. Only 1% of households at safe wells were early-switchers, while none of the households switched in both periods, yielding a short-term switching rate of 1% (Figure 2A), significantly lower than the 24% short-term

switching rates observed from unsafe wells. We also find that while 9% of the households with safe wells were late-switchers, 90% of these late-switchers had switched away from their BAMWSP-tested well due to reasons unrelated to arsenic. For one-third of these households, their BAMWSP-tested well had ceased to function. In Figure 2B, we focus on households who mention arsenic-related concerns, or lack thereof, for switching/not switching from their safe well and we now find that only 1 % of households tested safe are late-switchers. [5] This is contrast to 26% late-switchers observed for households tested unsafe who switched due to arsenic concerns. This difference is statistically significant, indicating that switching behavior is driven by arsenic-test results.

At the same time, socio-economic factors correlated to arsenic might drive switching behavior. However, the natural processes that determine spatially-varied arsenic levels have been demonstrated to be independent of such household characteristics (Madajewicz et al. 2007; Bennear et al. 2010). Nonetheless, we also control for socio-economic factors that may drive decisions to switch while examining the effect of well tests. In Table 3, we employ a probit model with the dependent variable indicating the household's decision to switch, using household characteristics and the

[5] These households mostly stated that the new well was safer than their previous safe well. BAMWSP only delivered results by painting wells red/green; due to lack on information about arsenic concentration of these wells, we are unable to verify whether the new wells are indeed safer.

BAMWSP test result as covariates, controlling for clustering[6] and sampling weights. While households' characteristics were measured in 2008, they are likely to be strongly correlated with those households' characteristics in 2003, permitting us to use these variables as controls while examining the impact of well testing on switching. We continue to find a positive and statistically significant effect of receiving an unsafe result from BAMWSP on the probability of switching source. These results echo the findings of previous work that demonstrates that provision of risk information motivates households to undertake behavior that reduces exposure to those risks.

2.3.4 Perceived well safety can change over the longer-term

Till now, we have inferred the switching impact of arsenic risk information provided through well tests by studying the roughly 80% of households with consistent perceptions about the arsenic-safety of their well through 2008. However, safety perceptions may change over time for a number of factors, including well paint fading away. In 2005, paint was observed on all 1557 wells, 1038 unsafe and 519 safe (Figure 3A).

[6] Clusters are defined by villages, and a households within a village is likely to be more similar to households within the same village that to households in a different village.

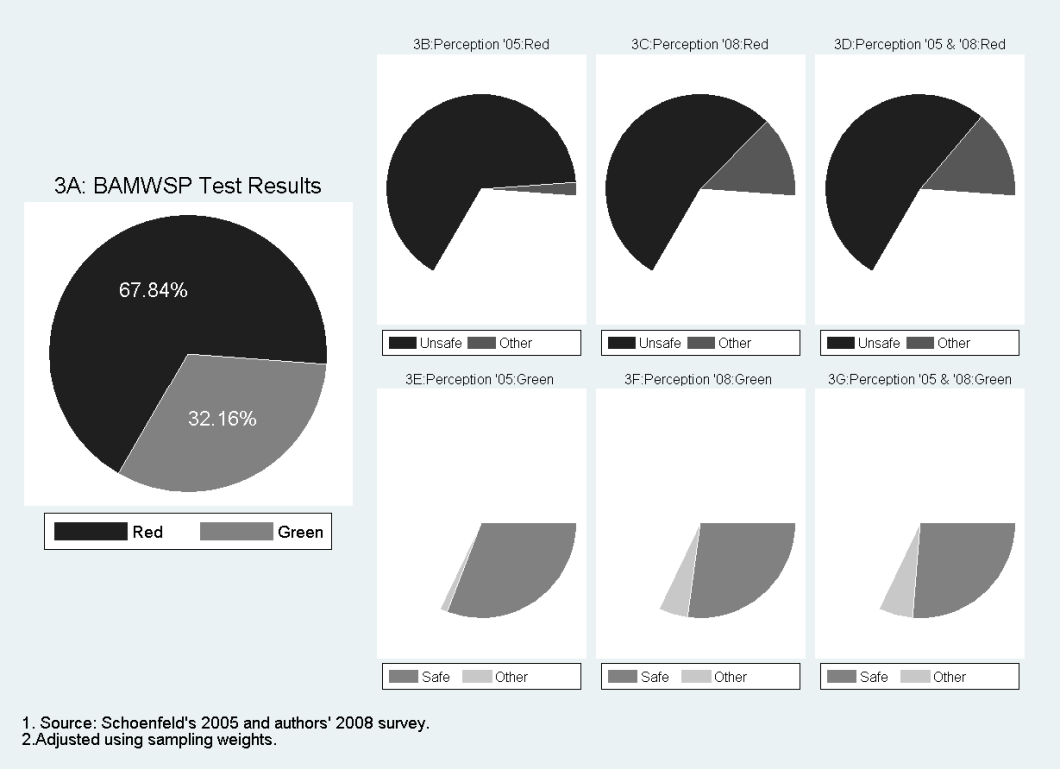

Figure 3: Recall of test results.

We find that 97% of unsafe-tested well owners (Figure 3B) and 96% of safe-tested well owners (Figure 3E) correctly perceived their well as unsafe and safe respectively in 2005. By 2008, the paint on almost all these wells had washed out, suggesting that perceived safety in 2008 may have changed especially once paint is not visible on the well. We find that 80% of unsafe-tested well owners (Figure 3C) and 84% of safe-tested well owners (Figure 3F) now correctly perceived their well's arsenic-safety status. Overall, 78% of unsafe-tested well owners (Figure 3D) and 80% of safe-tested well

owners (Figure 3G) continued to correctly perceive the arsenic safety of their well through 2008. These results suggest that while most households continue to correctly perceive the arsenic-safety of their tested well, some households do change their perceptions, especially after five years of testing.

We now focus on households whose safety perception of the tested well in 2005 line up with the test result provided by BAMWSP, but whose 2008 safety-perceptions don't. We have 54 such "tested safe but perceived unsafe" households (Table 2, column 16), and 91 "tested unsafe but perceived safe" households (Table 2, column 3) in our sample. We present the behavior of these households in Figure 4, below.

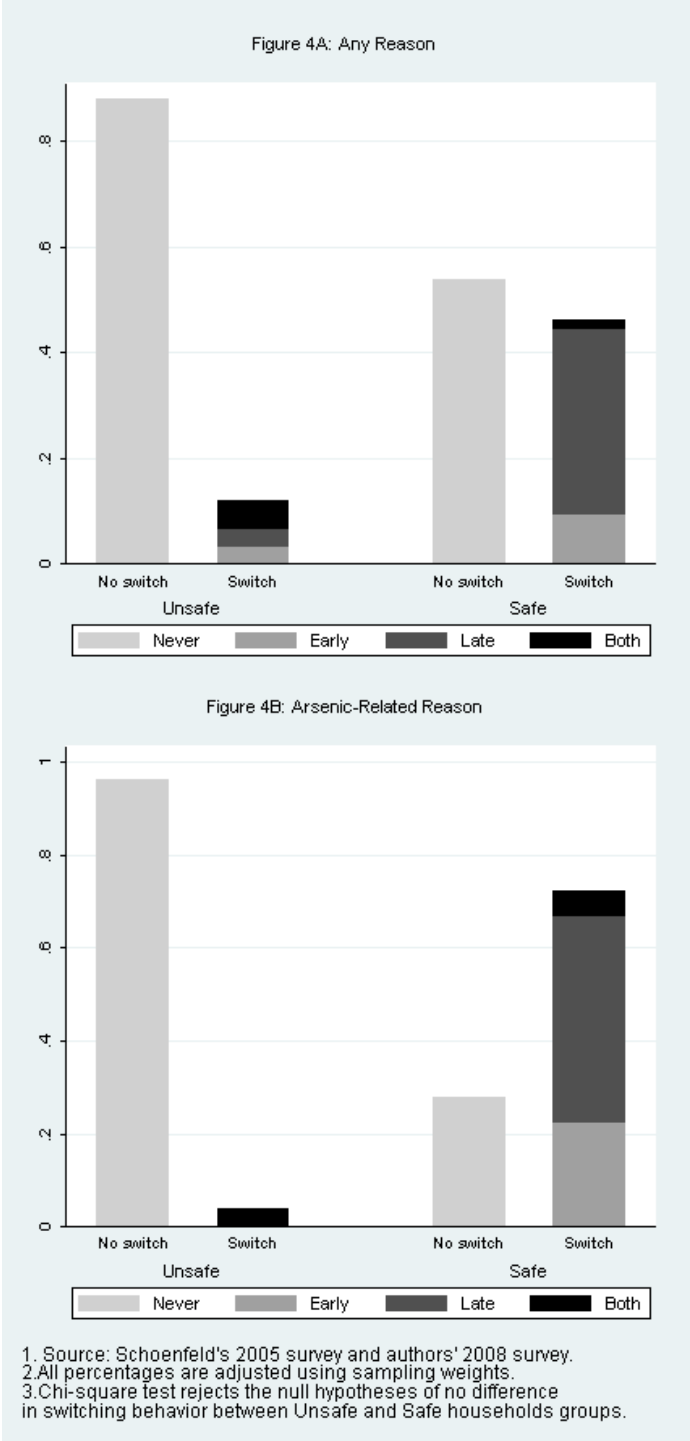

Figure 4: Switching behavior—households with incorrect status perception.

We find that 42% of "tested safe but perceived unsafe" households switched sources at least once, with most households switching late (during 2005-08), and only 10% of "tested unsafe but perceived safe" households switched sources by 2008. The differences in switching behaviors observed in Figure 4 are statistically significant between "tested unsafe but perceived safe" households and "tested safe but perceived unsafe" households. These results are exactly opposite to those observed in Figure 2A, where we examined households that consistently perceived the safety of their BAMWSP-tested well through 2008—42% of unsafe- tested households switched in contract to only 10% of safe-tested households. These results suggest that switching is driven by perceived safety, which can change with time.

Household behavior responds to perception of well-safety; however it is also possible that household behavior may influence its well-safety perception. In Figure 5, we consider households whose 2005 perceptions line up with the BAMWSP test result, but whose 2008 perception does not. We examine these households by their switching behavior in 2003-05 and change in perceptions in 2005-08.

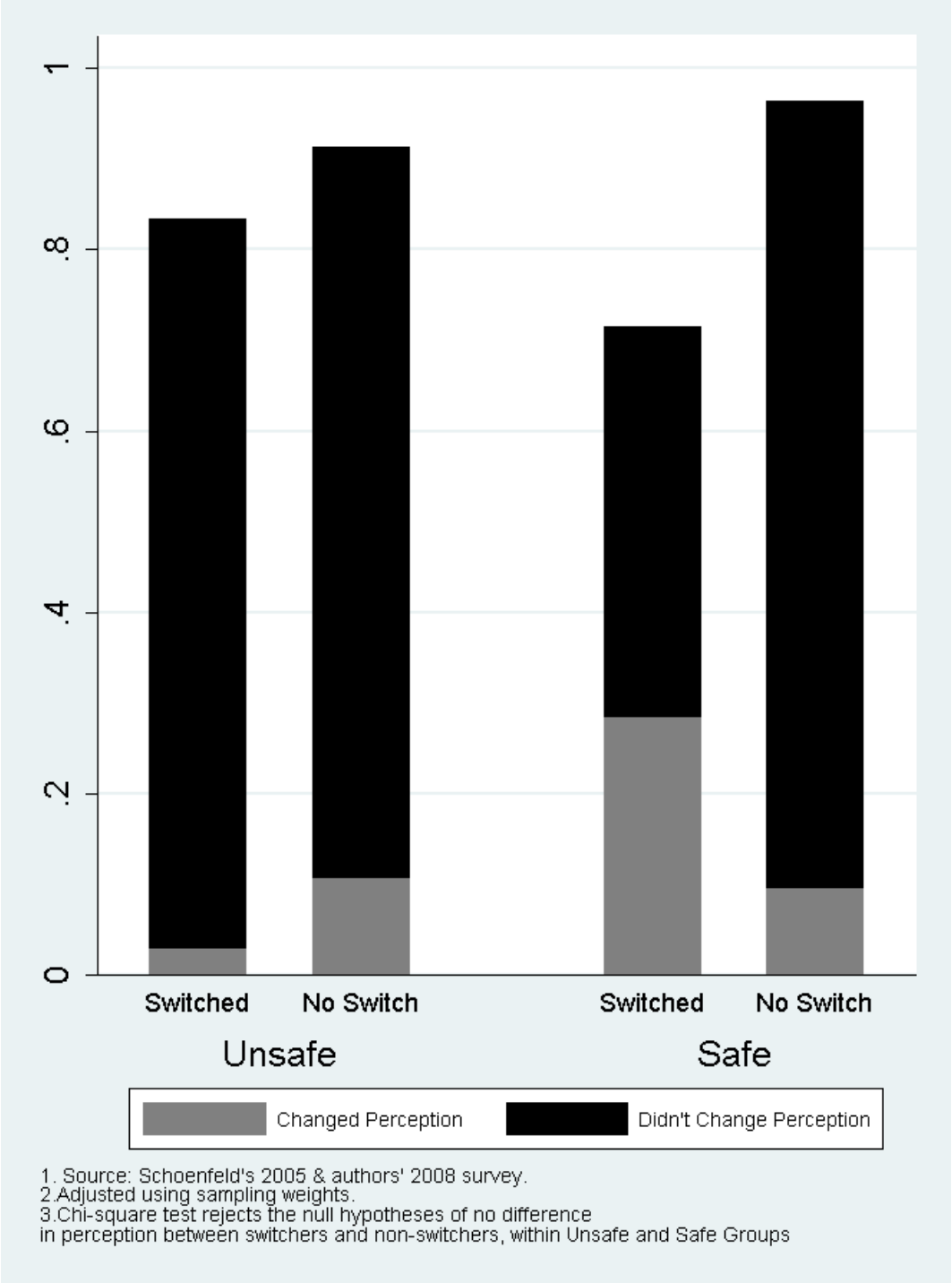

Figure 5: Behavior in 2003-05 and safety perceptions in 2005-08

For households tested unsafe by BAMWSP, we find that 12% of households that did not switch sources in 2003-05 perceived their BAMWSP-tested well as safe in 2008. In contrast, only 5% of households that switched sources in 2003-05 perceived their unsafe well as safe in 2008. This difference is statistically significant. Similarly for households tested safe by BAMWSP, 10% of households that did not switch during 2003-05 perceived their well as unsafe in 2008. This is in contrast to a significantly higher 50% of households switching sources in 2003-05 who perceive their well as unsafe in 2008. Both switching behavior and households' perception during 2005-08 were recorded simultaneously; this limits our ability to understand whether behaviors influence perceptions or perceptions influence behaviors. However, this observation demonstrates the importance of understanding household behavior in the light of its perceptions regarding the risks it faces

2.4 Discussion

We find overwhelming persistence during 2005-08 of the 2003-05 switching decisions made by households in Bangladesh, which reduced exposure to arsenic. Not a single household that switched during 2003-05 from a well tested in 2003 by BAMWSP as unsafe switched back. About 80% of the households that switched during 2003-05 simply stayed at their new wells. About 20% of early switchers switched again, but not back to their unsafe BAMWSP wells. We also find that the longer-term switching rate

from unsafe sources through 2008 (42%) is almost double than observed in the short term from unsafe sources through 2005 (24%). An additional 18% of households at unsafe wells did not switch during 2003-05 but did switch during 2005-08. Short-term and longer-term switching for arsenic reasons occur almost exclusively at unsafe wells, and differences in switching patterns between households whose wells were tested unsafe and those with safe wells is statistically significant. Controlling for socio-economic indicators, an unsafe test result continues to have a positive and significant effect on the decision to switch sources. These results suggest that not only has well-testing motivated exposure-reducing behavior in the short term, it has also motivated behavior beyond the short-term—between two and five years of testing.

Provision of arsenic risk information through the testing and labeling of wells is relatively inexpensive compared with other technological solutions like piped water and arsenic-treatment, yet it appears to have significant short-term impacts, and even larger impacts over the longer term. Yet the increasing gains from risk information over time have not entered policy debate, although our results strongly contradict prior questioning about the efficacy of well testing in reducing exposure to arsenic.

In Bangladesh, the option of reducing exposure to arsenic via well testing and information campaigns is not currently being given as much attention as more capital-

intensive interventions, such as centrally-supplied piped water piping. [7] Such modern capital intensity, while desirable, has yet to become a reality seven years after the formulation of the National Policy for Arsenic Mitigation in 2004. In the meantime, at least one-third of tubewells in Bangladesh are untested due to ongoing well installations. As a result, a significant portion of the rural populations continues to drink water from wells whose arsenic content is unknown, potentially exposing these populations to develop arsenic-induced illnesses like cancers, cardiovascular diseases and neurological impairments. Health risks from consuming arsenic-contaminated water do not dissipate immediately upon exposure, and risks are higher if exposures are longer. Given the epidemiology of arsenic, our results show that a lack of ongoing well testing will miss an easy opportunity to reduce exposures of populations now, thereby compromising the health of these vulnerable populations.

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[7] The National Policy for Arsenic Mitigation can be downloaded from the website of the Department of Public Health and Engineering, the nodal body for providing drinking water and other water-sanitation services. http://www.dphe.gov.bd/pdf/National-Policy-for-Arsenic-Mitigation-2004.pdf

Table 1: Summary statistics

	Mean	Std Dev
Income		
Household food consumption: monthly *	5019.68	3075.86
Household Expenditure : monthly*	6234.14	3272.39
Household expenditure on medicines: monthly*	538.39	991.41
Household Income: monthly*	8674.38	10547.39
Brick Walls	0.13	0.35
Sanitary latrine	0.85	0.35
Demographics		
Respondent age	40.39	13.24
Respondent female	0.98	0.14
Respondent primary water-source decision maker	1	0
Respondent literate	0.48	0.5
Family Size	5.44	2.36
# children	1.94	1.52
Fraction households with arsenic symptoms in at least one member	0.1	0.29
Fraction household members with primary education	0.62	0.27
Fraction household members with secondary education	0.32	0.29
# children in school per household	1.1	1.11
Social interactions		
Arsenic-induced illnesses: neighbors	0.06	0.24
Arsenic-induced illnesses: relatives same village	0.03	0.16
Arsenic-induced illnesses: relatives other village	0.01	0.09
Arsenic-induced illnesses: friends same village	0.01	0.08
Arsenic-induced illnesses: friends outside village	0.003	0.05
Arsenic-induced illnesses: village leader	0.003	0.05
Discussed arsenic risks: household members	0.51	0.5
Discussed arsenic risks: neighbors	0.28	0.45
Discussed arsenic-risks: relatives same village	0.14	0.36
Discussed arsenic risks: relatives outside village	0.05	0.24
Discussed arsenic risks: friends same village	0.05	0.23
Discussed arsenic risks: friends outside village	0.02	0.13
Discussed arsenic risks: village leader	0.01	0.09
Named households with tested wells (#)	1.56	1.03
Distance		
Distance to closest safe well (meters)	34.2	51.28

Notes:
1.Source: Authors' 2008 survey
2.All income and expenditures derived from simple one-shot questions.
3. All monetary units are in Takas; Purchasing power parity of 23 Takas per US$.
4. Means and standard deviations adjusted for sampling weights

Table 2: Perceptions of households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Paint Observed in 2005	R	R	R	R	R	R	R	R	R	G	G	G	G	G	G	G	G	G
Perception 2005	U	U	U	DK	DK	DK	S	S	S	U	U	U	DK	DK	DK	S	S	S
Perception 2008	U	DK	S	U	DK	S	U	DK	S	U	DK	S	U	DK	S	U	DK	S
# absolute	803	108	91	15	2	3	3	3	10	5	4	8	1	0	6	54	22	419
% paint observed	0.78	0.1	0.08	0.02	0	0	0.01	0	0.01	0.01	0.01	0.02	0	0	0.01	0.1	0.04	0.82
	Fraction of households that switched																	
Never	0.58	0.44	0.9	0.08	0	0.82	0.74	0	0	0.62	0.51	0.82	0	0	0.68	0.57	0.7	0.9
Only Early	0.19	0.2	0.04	0.47	0	0	0.26	0.82	0	0.21	0.22	0.1	1	0	0	0.08	0.04	0.01
Only Later	0.18	0.18	0.02	0.38	0	0.18	0	0	0	0	0	0	0	0	0.32	0.33	0.09	0.09
Early & Later	0.05	0.18	0.04	0.07	0	0	0	0.18	0	0.17	0.17	0.08	0	0	0	0.04	0.17	0.0
Switched back to BAMWSP tested source	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0

Notes:

1. Source: Schoenfeld's 2005 survey and authors' 2008 survey
2. R=Red; G=Green; U=Perceived Unsafe; S=Perceived Safe; DK=Don't know safety of well
3. All percentage adjusted using sampling weights

Table 3: Effect of BAMWSP test-result on switching behavior (controlling for socio-economic characteristics)

	Switch Ever vs. Switch Never	
	Marg. Effects	
Unsafe	0.38 (0.04)	***
Own latrine	0.04 (0.05)	
Brick walls	0.14 (0.04)	***
Monthly income (1000s)	-0.00 (0.00)	
Family size	-0.00 (0.01)	
Respondent age	0.00 (0.00)	
Primary decision maker literate	0.02 (0.03)	
Arsenic induced symptoms in at least one household member	-0.08 (0.05)	
Respondent literate	-0.03 (0.04)	
Fraction household members completed primary education	0.20 (0.07)	***
Distance to closest green well (kms)	-1.43 (0.52)	***
N	1100	
F Statistic	F(10,49)=13.97	
Prob>0	0.0000	

1.Source: Schoenfeld's 2005 and authors' 2008 survey

2. Households consistently perceiving the arsenic-status of well through 2008 used

3. Results from a probit model, adjusted for sampling weights and clustering at village level.

4. Standard errors in parentheses. *, ** and *** indicate estimates significant at 10%, 5% and 1% respectively.

3. Bright Lines, Risk Beliefs, and Risk Avoidance: Evidence from a Randomized Intervention in Bangladesh

3.1 Introduction

The use of health labeling and information disclosure policies is on the rise across many health policy domains. The explicit goal of these policies is to promote healthy behavior by increasing awareness and understanding of health risks associated with several forms of behavior. Examples of health labeling programs in the United States include the Nutritional Labeling and Education Act (NLEA) of 1990 which required uniform labeling of packaged foods, recent New York State law that requires fast food restaurants to post calorie counts on menu boards, campaigns that warn against excess fish consumption due to mercury, and campaigns promoting mitigation of lead and radon hazards in homes, among many others. Information-based policies have also been adopted in developing countries for the promotion of a wide array of health-related behaviors, ranging from HIV testing and prevention to the use of insecticide-treated bed nets or of cleaner sources of drinking water.

Despite the proliferation of such information-based public health policies, there is little agreement in the literature on how to present information in ways that best motivate health-improving behaviors. An issue that arises in many of these examples is how best to convey complex or multi-dimensional risks in ways that individuals can

readily understand and use in decision-making. Policies have run the gamut from providing extensive and unprocessed information (e.g., nutritional labeling) to reducing the risk information to simple "bright-lines" decision guidance (e.g., fish consumption advisories). But little is known about the relationship between risk presentation and behavioral responses that would allow policy makers to better craft and target health messages. In addition, many studies have found that information programs are often ineffective at promoting health-protecting behavior among the most at-risk individuals.

This paper contributes to this literature by studying the impact of information format on behavior in the context of a program promoting mitigation against health risks from arsenic in drinking water in Bangladesh. The natural occurrence of arsenic (As) in groundwater is an important public health concern in several countries worldwide, including in China, India and the United States. Nowhere, however, is the problem more serious than in Bangladesh, where in 1999 an estimated 35 million people (about 30% of the population) were habitually drinking shallow tubewell water that exceeded the Bangladesh standard for arsenic in drinking water (50 micrograms per liter or parts per billion (ppb)), while 57 million (45%) drank water with concentrations above the World Health Organization (WHO) recommended limit of 10 ppb. Long-term exposure to arsenic in drinking water has been linked to several health risks, including skin lesions, several form of cancers and cardio-vascular diseases, with a latency period

of 5 to 15 years for early health effects and 20 years or more for cancers (see Chen et al. 2007 and references therein). In Araihazar, Bangladesh Argos et. al (2010) estimate that drinking groundwater with > 150 ppb arsenic almost doubles all-cause mortality compared to drinking water with up to 10 ppb. Despite the magnitude of the problem, the spatial heterogeneity in arsenic contamination in several areas is so marked that users of unsafe wells live no more than 1-200 meters from safe (or at least safer) wells (van Geen et al. 2003). In communities where tubewells' arsenic contamination is known, well-sharing among households is then often a viable short-term mitigation strategy (van Geen et al. 2002). By 2005, about 5 million tube wells had been tested free of cost as part of the widespread Bangladesh Arsenic Mitigation Water Supply Program (BAMSWP, see Ahmad et al. 2006). Information was provided in a bright-line format, by painting the spout of the tested tubewells red or green depending on whether the arsenic concentration was above or below the national standard of 50 ppb. This information disclosure program has been a relatively inexpensive and effective mitigation strategy. In Araihazar district, in locations proximate to our study areas, earlier studies have documented high rates of switching off unsafe wells following the provision of information (Schoenfeld 2005; Ahmed et al. 2006; Chen et al. 2007; Madajewicz et al. 2007; Opar et al. 2007). Chen et al. (2007) found significant reductions

in urinary arsenic (a good indicator of exposure) among individuals who switched to safer sources in these areas.

Despite high levels of switching, there remain significant environmental health concerns. First, it is widely acknowledged that no known level of arsenic exposure is completely safe and that health benefits can result from any decrease in arsenic exposure. It is then cause of concern that the Bangladeshi standard is five times as large as the threshold adopted by the WHO and governmental organizations such as the United States Environmental Protection Agency (EPA). Second, decreased arsenic exposure from 400 ppb to 200 ppb yields significantly greater reduction in risk, than reducing exposure from 60 ppb to 30 ppb (NRC 1999; NRC 2001). However, the bright-lines risk presentation by BAMWSP encourages the second switch but not the first. A related concern is that a household whose well tests positive for arsenic at 49 ppb has no incentive to move to a nearby well that has 1 ppb arsenic, despite the potentially significant health benefits associated with that switch.

This paper provides evidence on the effects of risk presentation on health behaviors using data from a cluster randomized controlled trial in risk presentation regarding arsenic in drinking water in Araihazar district. The intervention was designed to test whether highlighting the existence of a gradient in arsenic risk—exposure risk increases with the level of arsenic and lower arsenic exposure is always

better—led to better choices relative to "bright lines" information provision that focuses on whether the arsenic level is above or below the country standard of 50 parts per billion (ppb).

We find that households that received the gradient message were 50% more likely to switch (35 vs. 23%) than bright-lines households when arsenic was in the moderately unsafe range (50-100 ppb) but 40% less likely to do so (28 vs. 47%) relative to bright-lines households for higher levels of arsenic which characterize most of the unsafe wells in the study area. There is no evidence that, conditional on switching, households receiving the gradient message chose safer sources. We use purposely collected information on risk perceptions to help explain these partly unexpected findings. Gradient households in the moderately unsafe range were more likely to perceive the tested water as unsafe, compared to households with similar arsenic levels who received the bright lines message. Among users of very unsafe wells (As>100 ppb) this pattern was reversed (but not statistically significant). While some of this difference in risk perceptions could be ex-post rationalization, we offer evidence that this does not explain all of the discrepancy. In the context of our intervention, providing richer risk information led to better health choices for a small segment of the study group and had no impact for the majority of the study-group.

This paper should be a useful contribution to the literature that studies how the format of health risk information affects individual behavior. The centrality of the format both in explaining risk and in influencing health-related behaviors has been long recognized in medicine and psychology (Edwards et al. 2000). Our result that richer information did not lead to better choices is consistent with studies on the impact of risk communication in genetic counseling, where some have suggested that knowledge about genetically-related risk factors may lead to fatalism and then discourage preventative behavior for some individuals (Marteau and Lerman 2001).

Our work is also related to a large literature that evaluates the use of simple thresholds in evaluating risk. For instance, since the 1970s, prenatal diagnostic guidelines in the United States and elsewhere have suggested that amniocentesis or other forms of invasive testing should be recommended only to women aged 35 years or older or, based on more recent advances, to women whose risk of fetus chromosomal abnormality are as high as that of an average woman in that age group (NIH 1979, Haddow et al. 1994).[1] However, this approach has been criticized because it ignores differences in couples' preferences, so that testing should instead be offered to all women irrespective of age (Pauker and Pauker 1994, Harris et al. 2004). Smith et. al

[1] The threshold was an estimate of the mother's age at which the risk of giving birth to a child with Down's syndrome was equal to probability of a procedure-induced miscarriage.

(1995) conducted a randomized experiment on household response to information on radon risk in homes. They found that the combination of qualitative information and bright-lines message was associated with higher levels of radon mitigation activity relative to quantitative risk information which provided richer, but also more complex, decision guidance.

More broadly this paper contributes to the literature on the health effects of health labeling and information programs, including nutritional labeling (Kim et. al 2000; Mathios 2000; Balasubramanian and Cole 2002; Neuhouser et. al 1999; Variyam and Cawley 2006; Harnack and French 2008; Downs et. al 2009; Wisdom et. al 2010) and food consumption advisories (Shimshack et al. 2007). These studies have found that nutritional information programs can improve health outcomes, but generally only for demographic groups that are at lower risk for diet-related chronic illness, including those with more education and higher income. One might expect that information programs are less likely to motivate change among populations for whom the information is more difficult to understand (proxied by education) or who have constraints that limit their ability to make different choices (proxied by income). If lower education and income are also correlated with higher risks, then high-risk individuals may respond less to risk-information campaigns. Our study also finds that high-risk households are less responsive to information campaigns, although in our context

higher exposure to As is not correlated with lower education or higher opportunity costs of switching (measures as the distance to the nearest safe well). So the usual rationales for the lack of impact of information programs on higher risk individuals do not hold here. We explore other explanations that focus on perceptions of risk.

In addition to complementing the literature in health labeling in the United States, this paper contributes to a growing literature on the potential role of information as a policy tool to improve health in developing countries. In a series of randomized controlled trials (RCTs) in Kenya, Tanzania and Trinidad, Coates et al. (2000) show that voluntary counseling and testing reduced self-reported at-risk sexual behavior significantly more than the provision of health information alone. Using experimental data from Delhi, India, Jalan and Somanathan (2008) find that households informed of the unsafe levels of fecal bacteria in their drinking water show an increased demand for clean water relative to a control group. Thornton (2008) uses data from an RCT in rural Malawi, and finds that awareness about HIV-positive status increased threefold the likelihood of purchasing condoms among sexually active individuals, although the number of condoms purchases remains very small. In a study carried out in western Kenya, Goldstein et al. (2008) estimate that learning one's HIV status has a marked impact on women's health-seeking behavior and investment decisions. In an RCT in Kenya, Dupas (2010) finds that girls exposed to information on the age profile of male

HIV prevalence led to sizeable changes in self-reported sexual behavior and to a 28% decrease in pregnancies, while no such impact was associated to standard abstinence-only HIV education curriculum. Jensen (2010) use data from the Dominican Republic to show that information about previously underestimated returns to education reduced drop-out rates among better-off students.

The paper proceeds as follows: Section 3.2 provides additional background on the arsenic problem in Bangladesh. Section 3.3 describes the randomized intervention and the data. Method and results can be found in Section 3.4 and we offer some interpretation of our findings in Section 3.5. The final section concludes.

3.2 Background: Arsenic in Bangladesh

During the 1970s, the Bangladesh government together with UNICEF, began encouraging Bangladeshis to switch from surface water sources of drinking water to shallow tube wells. The main purpose was to reduce exposure to bacterial contamination of surface water, which was associated with high rates of infant and child mortality (World Development Report, 2000/2001). Unfortunately, it later became known that groundwater in much of Bangladesh contains very high levels of naturally occurring arsenic. The switch to tube wells has exposed millions of Bangladeshis to highly toxic levels of arsenic and has been dubbed 'the largest case of mass poisoning in history' (Smith et al. 2000).

International aid agencies and the national government are actively seeking methods to reduce exposure to arsenic in drinking water. While solutions such as deeper (and safer) community wells are already implemented throughout the country, piped water-supply systems and arsenic-removal filters have not yet been shown to be practical on a sufficient scale (Ahmed et. al 2006; Ahmed et. al 2005). In the short-term, however, the largest reductions in exposure are attributable to switching between existing wells (van Geen et al. 2002). The reason that well-switching is a promising short-term policy is that arsenic has a fairly unusual feature among natural groundwater contaminants in that its concentration can vary substantially over a small spatial area (van Geen et. al 2003). A well with very elevated levels of arsenic may not be very far from a well that has low levels of arsenic.[2]

In 1998, the World Bank and the government of Bangladesh began a widespread program of testing and labeling tube wells called the Bangladesh Arsenic Mitigation Water Supply Project (BAMWSP). The tube wells were tested on site by field workers supervised by the Bangladesh Rural Advancement Committee (BRAC) using accurate arsenic field test kits and were offered free of charge. Wells with arsenic levels in excess of the Bangladesh health standard for arsenic of 50 ppb were labeled "unsafe" and

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[2] Deep wells tend to be more uniformly low in arsenic. However, the depth at which a well is likely to be safe varies from 30 meters to 120 meters in Arahaizar (van Geen et. al 2003, Gelman et. al 2004).

painted red, while those with arsenic levels below 50 ppb were labeled "safe" and painted green. By 2005, about 5 million tube wells had been tested under the program. Overall, it was estimated that about one-third of the wells were contaminated, therefore about 35 million people were thought to be consuming groundwater containing arsenic at concentrations greater than Bangladesh standard of 50 ppb and about 57 million people to be consuming groundwater containing arsenic at concentrations greater than World Health Organization standard of 10 ppb (BGS/DHPE 2001; World Bank 2005). At the same time as wells were being tested, BAMWSP also began a television campaign that explained the health effects of drinking arsenic-contaminated water and advocated switching to "safe" green wells for drinking water. [3]

Previous research in Bangladesh suggests that providing households with bright-lines (safe/unsafe) information on arsenic status of tube wells encourages widespread switching from unsafe to safe wells. In Araihazar district, Bangladesh (in locations proximate to our study areas), Madajewicz et al. (2007) found that, after controlling for confounding factors, households informed of the unsafe concentration of arsenic in their well water were 37 percent more likely to switch to a different source of drinking water within one year than others whose water tested safe. Using data from subsequent survey in the same areas, Opar et al. (2007) documented a 50 percent increase in the likelihood

[3] Somewhat surprisingly, TV ownership is extremely high even in rural parts of Bangladesh.

of switching water sources associated with the delivery of information about unsafe arsenic levels. Such large effects of information on behavior and health may have been facilitated by the fact that the area has been the subject of an intense interdisciplinary study led by the Columbia University Superfund Basic Research Program since 2000.[4] However, in neighboring areas not covered by the Superfund study, Schoenfeld (2005) documented a still remarkable 26 percent increase in the likelihood of switching to a different water source following the delivery of test results for unsafe wells. In chapter 2 of this dissertation, we found that previously documented switching behavior in Araihazar is persistent over time, with almost no households moving back to unsafe wells.

Despite the huge magnitude of the BAMWSP testing campaign, which officially ended in 2006, millions of wells remain untested (BRAC 2008). In fact, new wells are being privately installed every year, while close to no testing has been carried out outside of the BAMSWP project.[5] Although it is known that arsenic concentration

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[4] See, for instance, van Geen et al. 2002, van Geen et al. 2003, van Geen et al. 2003, Parvez et al. 2006 and Chen et al. 2007. The research program studies the health effects, geochemistry, and remediation of Arsenic and Manganese, primarily in groundwater. For more information see http://superfund.ciesin.columbia.edu/niehsWeb/index.jsp.

[5] The shallow tube wells that supply the vast majority of drinking water to rural households in Bangladesh can be sunk in one day at relatively low cost. A typical 50-feet (15m) deep well cost (in PPP) approximately 50 dollars (van Geen et al. 2003). Using the 2005 ICP World Bank PPP exchange rates, this corresponds to about 1,000 Taka (World Bank 2008. See in particular page 23 in http://siteresources.worldbank.org/ICPINT/Resources/icp-final-tables.pdf). For perspective, in our sample

typically declines with well depth, the "safe" well depth varies geographically and while substantial scientific progress has been made in modeling safe well depths (Gelman et. al 2004), these depths are usually unknown to the people digging new wells. In view of the possibility of future new testing campaigns, evidence suggesting which communication modes are more effective at inducing mitigating behavior can then be extremely valuable.

3.3 Description of the Data and Randomized Intervention

The study took place in a 100-km^2 area of Araihazar Upazila located approximately 30 km from the capital city of Dhaka. This region has experienced several rounds of arsenic testing. First, in 2003, BAMWSP conducted arsenic tests as described in Section 2 and painted wells red or green based on arsenic content. Further, the Columbia University Superfund Basic Research Program has had an active interdisciplinary research program in this area since 2000. Schoenfeld (2005) studied 75 villages in Arahaizar that had not been part of the intensive public health study initiated by Columbia University in order to test whether switching rates differed substantially in villages without a prolonged presence by the Columbia University Superfund team.

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we estimate that the median total expenditure per month per household at baseline was 5000 takas, that is, $220 in PPP terms.

While collecting the data on switching behavior analyzed in Schoenfeld (2005), field workers drew water samples from any new or previously untested well identified in the study villages. This led to water samples from 533 wells in 48 villages. Two villages were later excluded from the study because they were used to pre-test the survey instrument and train enumerators, while another was not visited because it only included a single tested well. Finally, two villages were visited at baseline but not at follow-up, because each village had a single well tested in 2005 and that well was no longer in use in 2008. Hence, overall the study uses data from a total of 43 villages that were not part of the Superfund project.

In 2008, we conducted a randomized intervention on risk communication as part of the effort to disseminate the results for the set of 533 wells discussed above. Our intervention focused on communicating information on the health risks from arsenic in drinking water to users of these wells. We randomly assigned villages to receive one of two different messages regarding arsenic in their drinking water. We chose to randomize at the village level in order to minimize information spillovers among households in the same village that received different messages. Villages were stratified

by union and randomly assigned to treatment or control within strata, by using a pseudo-random number generator.[6]

Unlike BAMSWP, which adopted the red-green painting to communicate safety levels, our team tagged the wells with a tin plate designed within the Columbia University project. Figure 6 provides a picture of a test result plate which shows that its most visible component is a pictorial information on whether the well is suitable for drinking. The plate shows a hand holding a drinking cup that is covered by a large cross when the arsenic level is above 50 ppb (as in the case of the well depicted in the figure). The plate also indicates the year when the water sample was collected and the specific arsenic concentration detected in the water tested from that well.

[6] Unions are the third highest level of geographic administrative aggregation in Bangladesh. Villages are the smallest units, followed by mouzas that contain 2-3 villages on average, and then unions which contain a collection of mouzas.

Figure 6: Tubewell and test result plate

The metal plate also indicates the well ID, which was used to match the test results to the tube-wells, together with geographical coordinates and records of the tube-well owners' names. The unique identification number and the geographical coordinates were used to verify whether the tube-well that was sampled was the same tube-well for which results were being distributed. This step was crucial because tube-well owners sometimes use pipes and hand-pumps from their old wells to dig a new well without removing the identification plates. Relying only on the identification numbers to identify the wells might have been misleading, because the arsenic results are relevant only for the well at the location from where the water was sampled and the results were only delivered in case of concordance.

The intervention varied how the results were orally communicated to households. Households in the "control" villages received a bright-lines message similar to that used by the Government of Bangladesh, as well as by the Columbia University team. The English translation of the message read as follows:

The national safety standard in Bangladesh is 50 ppb (again, that is micrograms per liter). That means the federal government says drinking water with more than 50 ppb arsenic is not safe. When possible you should seek to fetch drinking water from a well that is labeled safe.

Households in the "treatment" villages received a message that also provided the government standard but emphasized that if the household has a choice between two or more wells they should choose water from the well with the lowest level of arsenic, even in situations where all wells have the same binary safety status. Specifically, the message read the follows:

The national safety standard in Bangladesh is 50 ppb (again, that is micrograms per liter). That means the federal government says drinking water with more than 50 ppb arsenic is not safe. However, we want to emphasize that whatever the level of arsenic in your drinking water now, if you have a choice of water from several wells it is better to drink water from the well with the lowest level of arsenic. For example, if you have a choice between a well with 200 ppb arsenic and a well with 100 ppb arsenic, drinking water from the well with 100 ppb arsenic is better for you. If you have a choice between a well with 40 ppb arsenic and a well with 10 ppb

arsenic, drinking water from the well with 10 ppb arsenic is better for you. When possible you should seek to fetch drinking water from the well with the lowest arsenic level.

We refer to this alternative treatment as the gradient message. We have 23 bright-lines villages and 20 gradient villages with 266 bright-lines households and 267 gradient households, respectively.

3.3.1 Description of the data

The data used in this paper were collected in two separate household surveys carried out in 2008. The baseline survey was completed between February and April 2008, hereafter we refer to this survey as the Wave I survey. While administering the Wave I survey, we delivered the results of arsenic tests to the households that used the wells which were sampled in 2005. As explained above, wells were identified based on information on the owner's name as well as on global positioning system (GPS) data. Interviews were then completed with the household who owned the well and also with another household who used the same well, if present. The respondent from the owner household was asked to name any other households who used the same tube well. Names were recorded in the order mentioned by the respondent and the enumerator approached the households in the order listed and interviewed the first available "user" household. In all cases, the interview was attempted with a female adult respondent and whenever possible with the wife of the household head.

In November 2008, we completed a second survey to assess household responses to the information on arsenic that was presented in the spring. We refer to this second survey as the Wave II survey. We attempted to conduct the Wave II survey with the same respondent who had completed the survey in Wave I. Data used in this study were restricted to include only respondents using a well that had not been moved from the original tested location, who were using the tested well as a source of drinking water when we administered the Wave I survey, and who completed the Wave II survey. Of the initial sample of 533 tube-wells, 434 tube-wells were located in our 43 villages in their original location. We surveyed 668 households using those 434 wells in Wave I. Of the 668 households that received well test results, 596 were using the tested tube-wells as their primary drinking-water source at the time of our Wave I survey. The Wave II survey was completed for 533 households of those 596 households (that is, 89% of the sample). To summarize, our sample consists of a balanced panel of 533 households that completed the Wave I and Wave II surveys and who were using the tested well as the primary source of drinking water when we administered the Wave I survey in Spring 2008. Attrition was balanced across experimental arms (12% in bright-line vs. 9% in gradient communities) and in both groups it was about 2 percentage points higher among users of unsafe wells, although the difference is not statistically significant.

Table 4 reports selected summary statistics measured at baseline for the 533 households in our sample. Overall, households in the sample are relatively large (5.3 members on average), with low education and relatively low income and expenditure. [7] For perspective, the mean total monthly household expenditure corresponds to approximately 262 USD, using a purchasing power parity exchange rate of 22.64 Bangladesh Takas (BDTs) per USD. Only 33 percent of household heads are literate and 21 percent have achieved at least a secondary school diploma, although enrolment rates among 6 to 14-year old is relatively high, at 76 percent. Most households (80%) make regular use of a sanitary latrine and 11 percent live in a "pukka" (good quality) dwelling.

The mean level of arsenic is 116 ppb, more than twice the threshold used by the Government of Bangladesh to identify "unsafe wells". There is also considerable variation within the sample, as shown by the standard deviation equal to 149. While the high mean is partly driven by some wells with very high levels of arsenic, the median is very high as well (80 ppb) and 61 percent of the tested wells had unsafe levels of arsenic. Consistent with the commonly found haphazard geographic distribution of arsenic (Van Geen et al. 2003, Chen et al. 2007), we find remarkable heterogeneity in arsenic

[7] Income and expenditure data are measured using simple, one-shot questions, so these estimates are likely to be measured with considerable error.

contamination even within villages. The heterogeneity is evident in Figure 7, which maps the study area and shows the location of safe and unsafe wells over the territory. Dots in green depict wells that have arsenic concentrations of less than 50 ppb. Dots in red depict wells that have arsenic concentrations greater than 50 ppb.

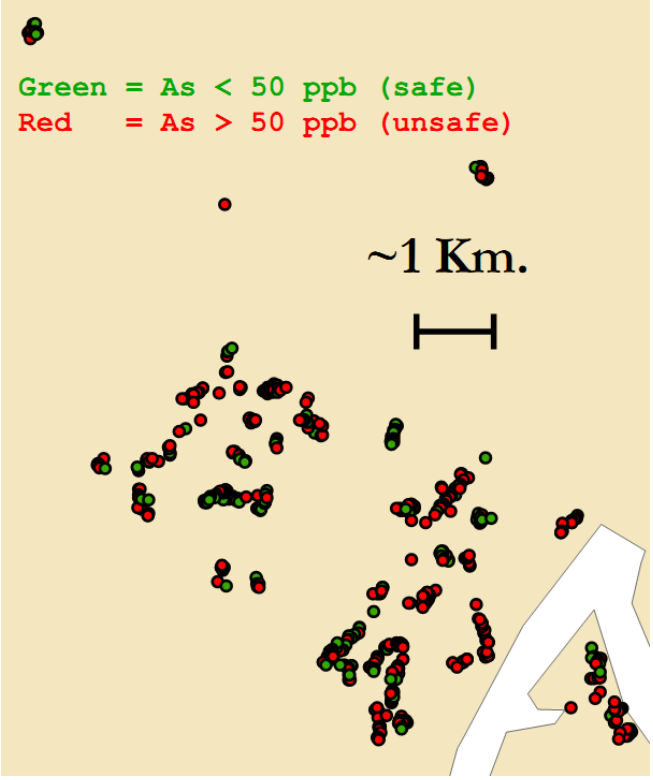

Figure 7: Spatial distribution of arsenic in study area

Despite high levels of arsenic, few households exhibit symptoms of arsenic poisoning. In less than four percent of households (and for 1 percent of individuals) we find anyone reporting any symptoms of arsenic poisoning. In almost all cases, such symptoms consist of skin lesions.

We have GIS coordinates for all wells used in this study and all wells tested by BAMWSP in 2003. For all of these wells, field workers also recorded whether the arsenic content was above or below the national standard (50 ppb) which allows us to calculate the distance to the nearest known safe well from each well in our sample.[8,9] The specific arsenic content of the well is only known for the subset of wells whose tests results were delivered in April 2008. For each well we can therefore calculate the distance to the nearest well that is known to be safer. Note that, even though we do not have the complete set of arsenic levels for all wells in the village, the information in our data set should coincide with the information used by respondents in deciding where to fetch water, because the actual arsenic content of the BAMWSP tested wells is known neither to us nor to households in the study area. In fact, recall that BAMWSP did not communicate the exact arsenic level but only labeled tested wells using the red-green binary format. The average distance to the closest well below 50 ppb is 75 meters and the average distance to the nearest well with lower arsenic is 86 meters. All distances are measured as-the-crow-flies.

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[8] Wells that are safe are given a distance of zero.

[9] There have been new wells dug since 2005 and some of those wells may have been tested by private companies. Private testing is rare, however, and no additional testing were done by BAMSWP or Columbia University in this area after 2005. So, although it is possible that there may be a few tested wells that are not in our sample, we do not expect there to be many. Hence, the closest safe well that is know to us is very likely to be the closest safe well that is known to the household.

We also asked respondents about other households they knew whose wells were tested in the past. The variable "network size" captures how many neighbors the respondent was able to recall whose well they knew had previously been tested. On average, households knew one other household with an arsenic test (mean=1.3).

An important component of the survey instrument was designed to measure perceptions about the health risks posed by arsenic. Beliefs about arsenic risk were elicited by posing a series of questions to the respondent about future events—asking respondents to express how likely they thought the described event would occur by counting physical objects. Each respondent was given 10 marbles and a plastic cup and asked to put more marbles into the cup if she felt the perceived event was more likely. After each question was asked, the cup was emptied so that the respondents started each question with 10 marbles and an empty cup.[10] This method was used to elicit respondents' beliefs about health risks from drinking arsenic from a generic hypothetical "unsafe well." Each respondent was asked to think of a well that had "just the amount of arsenic that the government says is unsafe." She was asked to think about a family that had been consuming arsenic-free water so far, but had switched to this hypothetical "unsafe" well on the day of the interview. The respondent was then asked about the

[10] Similar methodologies for eliciting beliefs have been successfully adopted in other low-literacy context and are becoming more commonly used in surveys. See Delavande et al (2010) for a survey of their use in developing countries.

chances that an adult from this family would develop skin lesions by drinking water from this well within alternative time horizons of 1 month, 1 year, 5, 10 or 20 years. She was also asked similar questions about the chances that an adult would develop "serious health problems," defined as health complications that would impede normal daily activities. The same questions were asked in the Wave I and Wave II surveys. In the baseline interview, these generic-well beliefs were elicited before the respondent was given her well test results.

In general, the beliefs data indicate that households understand the cumulative nature of arsenic risk. Mean levels of concern increase with time of exposure. Moreover, concern levels are relatively high for serious health consequences over long time horizons. The average subjective probability of an adult developing serious health consequences after drinking unsafe water for 10 years was 67% and over 20 years was 89%. In columns 5 and 6, Table 4 also contains differences in means of observable characteristics among treatment and control households and the p-values of the tests of equality between groups. The tests, like all the regression estimates that will follow in the paper, are robust to the presence of intra-village correlation. Randomization was overall successful in balancing the 23 observed characteristics among experimental arms. The null hypothesis of equality between arms is never rejected at the 5% level, and in only one case (mean value of food monthly consumption) at the 10% level.

Importantly, there are no statistically significant differences in arsenic levels between arms. The difference in mean arsenic levels between the two groups is 16.5 ppb (p-value 0.6). Even though the mean arsenic levels are similar we may be worried about other differences in the arsenic distribution between treatment and control households. Figure 8 provides the distribution of arsenic for the two groups and the distributions look quite similar.[11]

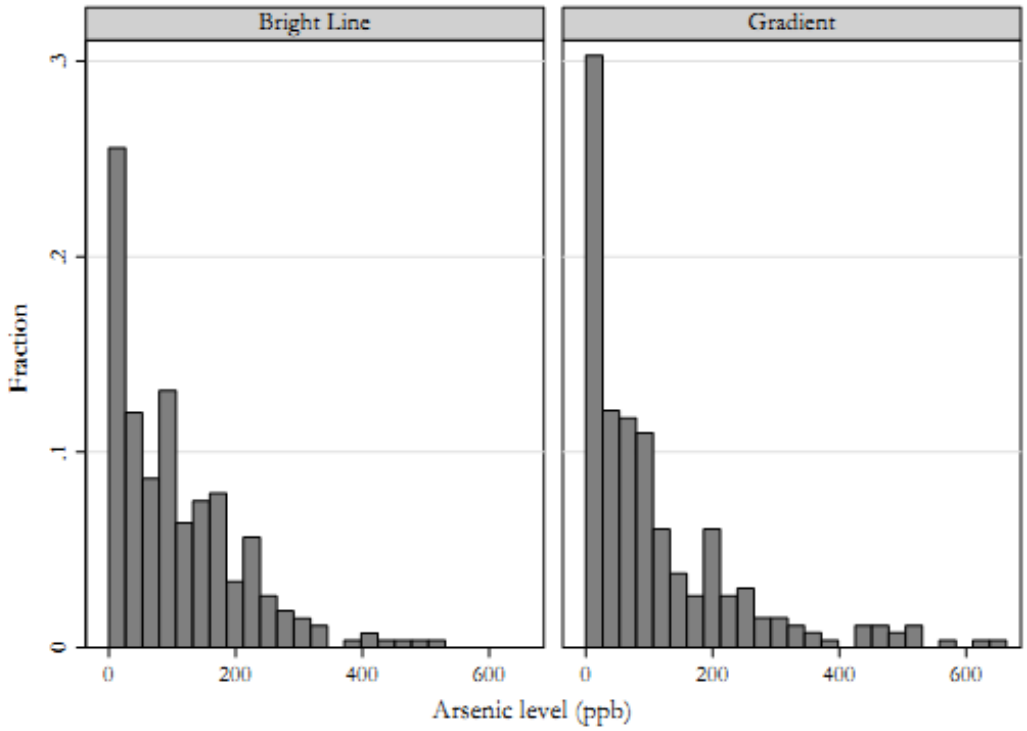

Figure 8: Histogram of arsenic levels by treatment

[11] The levels of arsenic were truncated at 750 to allow for clearer comparisons of the distributions. Only three households were affected by this truncation and all three are in treatment villages.

To test for equality of the distributions more formally, we divided arsenic levels into six bins and ran a Pearson's chi-squared test.[12] The p-value on the test is 0.52 indicating that we cannot reject the null hypothesis of equality of the arsenic distributions. The null is also not rejected if we test the equality of distributions only for unsafe wells (p-value=0.14).

3.3.2 Outcomes of the Intervention

The primary outcome of interest is whether households that receive the continuous risk message are more likely to move away from an unsafe source of drinking water. In the Wave II survey, households were asked whether they continued to use the well they had been given results for. If the respondent said her household was now getting drinking water from a different source, then the variable SWITCH was coded as a 1 and if the household was using the same well the variable SWITCH was coded as a 0. Of the 326 households using wells with arsenic greater that 50 ppb, 115 (that is, 35 percent) switched sources. Of the 207 households using wells with arsenic less that 50 ppb, only 15 (7 percent) had switched. When a respondent said they were using a new source, the survey enumerator actually went with the respondent to the

[12] The intervals that delimit the bins are as follows: [0,0.1], (0.1,50), [50,100), [100,200), [200,400) and As>400ppb.

new source. Thus, we feel confident that self-reported switching actually measures real changes in behavior. Indirect evidence supporting this view is also provided by earlier studies completed in areas proximate to our study locations, which showed significant declines in arsenic exposure (as measured through urinary arsenic concentration) in households who reported having abandoned the use of an unsafe well for drinking water (e.g. Chen et al. 2007).

An additional important question, which cannot be addressed with the binary switching outcome, is whether the gradient message affected the "quality" of switches, by enabling households to seek water from wells with the lowest level of arsenic. To examine this we would like to compare changes in arsenic exposure in gradient and bright-lines villages. However, in our sample we do not know the change in arsenic exposure for all households that switch water sources. The enumerator accompanied the respondent to the new source of drinking water and recorded any available information on arsenic. The records include the actual arsenic level (if the source was a well tagged with a tin plate) or the color of paint on the well spout (if visible). Of the 125 households that switched wells between Wave I and Wave II, we know something about the arsenic level for 49 of them (just under 40%). Among those 49 wells we know the actual arsenic level of 25 and the color of the well for 24. We then categorize the switch as "beneficial", "harmful" or "unknown". If we know the arsenic level of the new well

then we compare the arsenic level of the new and old well to determine whether the switch was beneficial or harmful. If we only know the color of the new well then we code the switch as beneficial if the old well had an arsenic level greater than or equal to 50 and the new well is painted green, while we code the switch as harmful if the old well had an arsenic level less than 50 and the new well is painted red. If the old well had an arsenic level greater than or equal to 50 and the new well is painted red then we categorize the switch as unknown (same if the old well was below 50 and the new well is green). Finally, we also categorize the switch as unknown if the household switched to a new well for which we have no information.

Even when we do not know the actual arsenic level of the new well, we might be able to make some inferences on whether the switch is health-beneficial. For example, if a household switches from a well at the 99th percentile of the arsenic distribution, a move to a different well, even if the new well were chosen randomly, would very likely lower the household's arsenic exposure. Based on this intuition, we construct a simple village-specific model of arsenic in order to estimate changes in arsenic exposure for all households who switch to a new well. Changes in arsenic exposure were calculated directly for households for whom we knew the actual arsenic level of the new well. For households for whom we do not know the actual level, but do know the color, we assign to the new well the median level of arsenic in that village for that color. In other words,

if the new well was red, we impute the median arsenic level for all wells in that village with arsenic above 50 ppb. If we know nothing about the new well we assign the well the median level of arsenic for the village. Thus, for every household that switched wells we have an estimate of the change in arsenic exposure. We use this estimate as an additional outcome.

3.4 Methods and Results

3.4.1 Well Switching Choices

We first use linear probability models to examine switching decisions. Our main regressor of interest is whether the household received the gradient message. We also include in our base specification the level of arsenic in the well, and we hypothesize that the higher the level of arsenic the more likely the household is to switch wells, consistent with the findings in Madajewicz et al. (2007) and Opar et al. (2007). We also include an interaction term between gradient and arsenic level that allows for the effect of the gradient message to vary over different levels of arsenic. In theory, our risk communication message could affect the frequency of switching among households that use wells with any positive level of arsenic. Indeed, one of the motivations for the emphasis on the gradient in arsenic risk was to encourage people using "safe" wells to lower their arsenic exposure further. However, we find very little switching among households using wells with less than 50 ppb arsenic (safe wells). Specifically, there are

only 15 of 207 households (7%) with arsenic less than 50 ppb that switch sources. Of these 15 switches, only 3 claimed to have switched wells for reasons related to arsenic (2 households in bright-lines villages and 1 household in a gradient village). Thus, even though treatment could have an effect in that part of the arsenic distribution, our data lack sufficient power to test for the existence of such an impact. We therefore focus on explaining switching behavior among households who were using an unsafe well at baseline, who are anyway the most exposed and therefore relevant population. Our specification is given by:

(1)

$$SWITCH_{iv} = \beta_0 + \beta_1 GRADIENT_v + \beta_2 \ln(As_{iv}) + \beta_3 GRADIENT * \ln(As_{iv}) + \beta_4 X_{iv} + \varepsilon_{iv}$$

where $SWITCH_{iv}$ is a binary variable that takes a value of 1 if the household i in village v switched wells after being informed about the (unsafe) status of the well in April 2008, $GRADIENT_v$ is the binary variable that takes a value of 1 if the household is in a village that was assigned to the gradient message, As_{iv} is the arsenic level of the household's tested well, X_{iv} is a vector of covariates (like income, literacy of respondent, assets etc) and ε_{iv} is the error term.[13]

[13] One concern about linear probability models is that it may produce predicted probabilities that are outside the unit-interval. For the switching model, all of the predicted probabilities are within the unit interval.

The interaction term in equation (1) allows for the effect of treatment to differ across the arsenic distribution. In principle, differences in arsenic levels could be correlated with different forms of unobserved heterogeneity, if households were sorting on arsenic level. In locations proximate to our study areas, Madajewicz et al. (2007) find no evidence of correlation between arsenic and several observed covariates. In Table 5, we show how tubewell arsenic levels, or a dummy for "unsafe well" (that is, As > 50 ppb), correlate with a series of household characteristics. There is a weak relationship between household characteristics and both unsafe status and the precise arsenic level. The R-squared on the regression is only 0.03 in both regressions and we cannot reject the null hypothesis that all slopes are equal to zero in both models. The monthly amount spent on food is statistically significant in the unsafe regression, although the coefficient is small. Increasing monthly food expenditure by 3,000 Takas (about one standard deviation) decreases the probability of using an unsafe well by 6%. In the model on arsenic levels, the age of the head of household is statistically significant, but again relatively small. Increasing the age of the head of household by 1 year increases the arsenic level by only 1 ppb. Overall, the poor fit of a model including many important observed covariates provides little evidence of sorting on arsenic and we conclude that the interaction of gradient and arsenic can be treated as exogenous.

The results of the impact of the gradient message on well switching can be found in Table 6. The first column contains the base specification that includes the gradient variable, the level of arsenic in the well, and the interaction of gradient with the arsenic level. For households in the bright line group, the probability of switching increases the higher the level of arsenic in the well. An increase in arsenic from 50 to 100 ppb is associated with a 19 percentage-point increase in the probability of switching to an alternative source. The effect of the risk message intervention is more complicated. The coefficient for the gradient message itself is positive and significant, but the interaction with the (log of) arsenic level is significant as well. The model predicts that households just at the safety threshold of 50 ppb were 22 percentage points more likely to switch with the gradient communication mode relative to those in the bright line group. However, with a high arsenic level of 200 ppb, the difference in predicted switching rates reverses sign and becomes -0.22. The value of arsenic where these two effects cancel out (so that the effect of the gradient message is exactly zero) is 101 ppb. Given that the median value of arsenic (for the unsafe part of the distribution) is 138 and the mean is 181, the effect of the gradient message is then negative for most households.

Because the estimates may be partly the result of the choice of a specific simple parametric model, we also evaluate the impact of the gradient message using non-parametric methods. We estimate switching rates conditional on arsenic using non-

parametric locally linear regressions (Fan 1992). We choose a relatively small bandwidth (equal to 50 ppb) in order to highlight the data-driven shape of the regressions. For each regression, we also display 90% confidence bands estimated using 250 bootstrap replications. We use block-bootstrap to reflect the clustered nature of the data, so that in each replication we re-sample clusters of village-specific observations rather than households. For each point on a grid of arsenic levels, we construct the lower and upper bounds of the 90% confidence band by selecting respectively the 5th and 95th percentile from the bootstrap distribution of 250 point-specific estimated regressions.[14] The non-parametric regression of switching decisions as a function of arsenic for bright-lines and gradient villages are shown in the top two panels of Figure 9.

[14] The bands are very similar if we estimate the upper and lower bounds by adding and subtracting 1.645 times the As-specific standard deviation of the 250 bootstrap estimates.

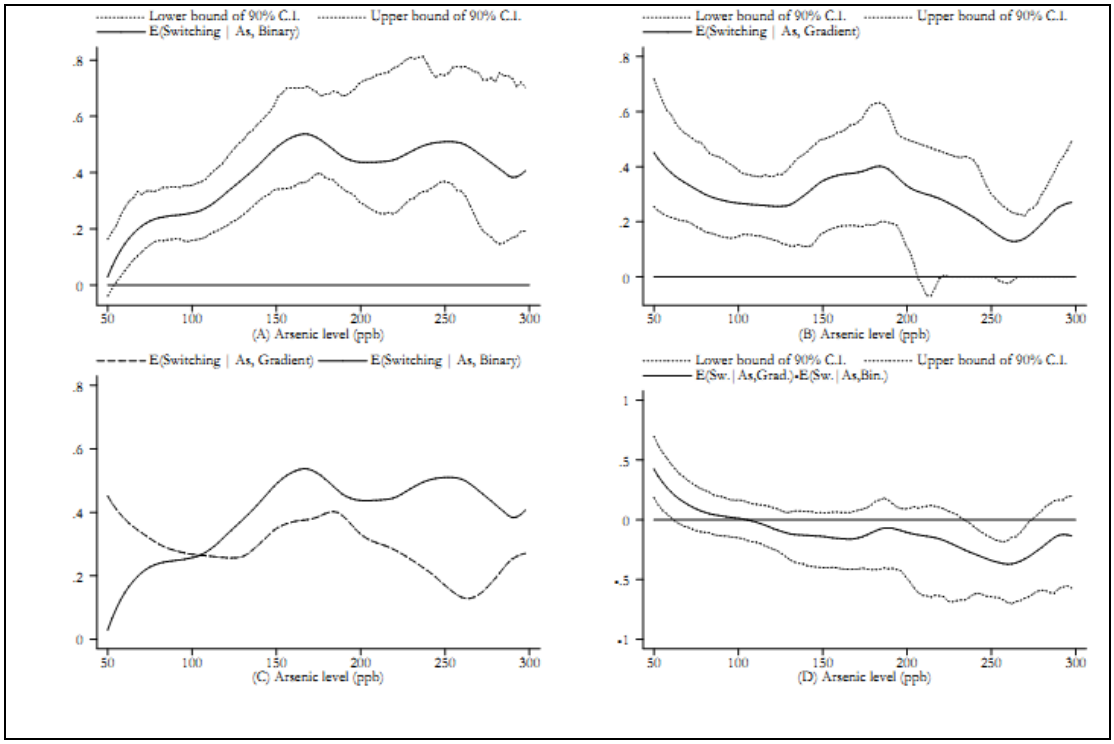

Figure 9: Non-parametric estimation of switching decisions

In areas where the bright-lines message was used, switching rates are close to zero at arsenic levels close to the safe threshold of 50 ppb, and only become substantially larger than 20% for arsenic levels above 100 ppb. Switching rates then increase visibly with arsenic levels up to 160 ppb and then stabilize around 40-50%. The shape of the regression is significantly different in gradient villages. First, almost half of households are estimated to switch for arsenic levels close to 50 ppb, which actually represents the peak over the arsenic range in the graph. Second, we find no evidence of increased switching for higher levels of arsenic. On the contrary, the regression suggests declining switching rates for high levels of arsenic. The stark difference between the two lines is

highlighted in panel C of Figure 9, where we display both regressions. Finally, in the bottom-right panel D, we display the difference between the gradient and binary regressions together with 90% confidence bands. The difference shows a marked declining pattern relative to arsenic levels. Although estimation error is large enough that we cannot reject the null of equality over most of the arsenic range, the difference is positive, large (about 40 percentage points) and statistically significant in a neighborhood of the safety threshold of 50 ppb and negative, large (about 35 percentage points) and significant for high arsenic levels around 250 ppb.

Overall, the non-parametric estimates are consistent with the OLS results in Table 6 and again suggest that the different risk communication messages led to strikingly different behavior among users of moderately unsafe and very unsafe wells. To ensure that these results are robust we try several other parametric specification and the results can be found in columns 2-4 of Table 6. In the second column, we show that the inclusion of several observed household characteristics leaves the results essentially unchanged. This robustness check is important, because although randomization should balance observed and unobserved covariates across the whole sample, the balance is less likely to hold along all parts of the arsenic distribution in a small sample. If that is the case, the treatment interaction may actually measure differences in covariates. Columns 7 to 10 of Table 4 compare the means of observed covariates among gradient and bright-

line households separately for households using moderately unsafe or highly unsafe wells. There are, in fact, a number of statistically significant differences in mean levels of observed covariates once we restrict the sample to these categories. Among users of moderately unsafe wells, the mean level of arsenic for gradient households is five ppb lower than for bright-line households (p-value = 0.063). However, the magnitude of the difference is small. The null of equality is also rejected at the 10% level for literacy, number of females in the household, fraction of children enrolled in school, well network size and availability of a sanitary latrine. Among users of highly unsafe wells, we find that statistically significant differences for medical expenditure (lower in bright-line households) and also in arsenic levels, where the mean is on average 79 ppb higher in wells from gradient communities. Note that if anything this latter fact should have expected to lead to a relative increase in switching, while we find that gradient households using highly unsafe wells are less likely to change source of drinking water relative to others in bright-line communities.

We also examine whether differences in prior subjective arsenic-related health risk perceptions from arsenic can explain the treatment effect findings. In column 3 of Table 6 we include two measures of risk perceptions. The first is a short-term measure which is the average of the respondents' answers to questions about the likelihood that an adult would experience "serious health problems" from drinking water from a

generic unsafe well over a one month and one year period. The second measure is a long-term measure which is the average of the respondent's answers to questions about the likelihood that an adult would experience "serious health problems" from drinking water from a generic unsafe well over a 10 year and 20 year period. We also include both these terms interacted with the log of arsenic. Only one of the risk measures is statistically significant—households with higher levels of concern about the long-term health effects of arsenic and who have higher levels are arsenic are more likely to switch. However, including these perception measures in the regression does not change the pattern of the intervention impacts.

The inclusion of additional covariates addresses potential differences in observed characteristics, but we might still be concerned about unobserved heterogeneity at the village level. Since we cannot use village-level dummy variables in a model with village-level treatments, we explore this possibility in other ways. First, we look at geographic patterns of switching behavior among respondents using an unsafe well at baseline. Figure 10 presents the percentage of households that switch by village, where the orange circles represent treatment villages and the blue circles represent control villages. The larger the circle, the higher the percentage of households using an unsafe well at baseline that switched to a new well.

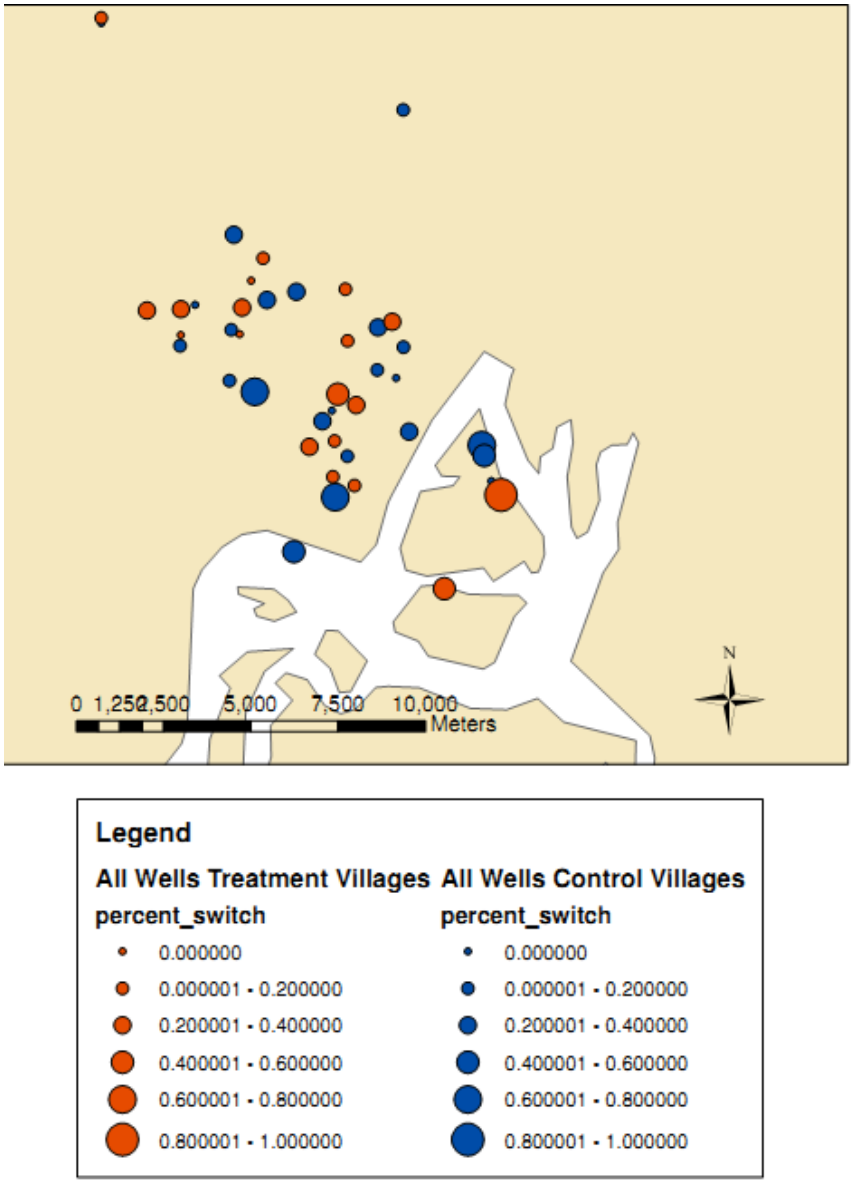

Figure 10: Spatial distribution of households switching off unsafe wells

Switching does happen across the study area, but there a few areas where high levels of switching appear to be spatially clustered. To control for unobservable covariates that might determine switching behavior in some spatially correlated way, we

include strata dummy variables. This will capture most of the spatial clustering that we can see visually on the map. These results are presented in column 4 of Table 6. The estimated effect of the intervention remains substantially unchanged, although both the relevant coefficients are closer to zero relative to the basic model in column 1.

Overall, then, with respect to switching decisions, it appears that receiving a message emphasizing the gradient between arsenic exposure and arsenic risk and encouraging the selection of a well with lower levels of arsenic does not have a uniform effect. Receiving the gradient message increased the likelihood of switching only for a small set of households with moderately unsafe arsenic levels (50-100 ppb). For households using water from these wells, switching rates are 35 vs. 23% for the gradient and bright line communication mode respectively. That is, switching rates are about 50% higher in gradient relative to bright-line areas, although the difference is not significant at standard levels (p-value=0.276) Among households with higher arsenic exposure, the rates are instead 28 vs. 47% in the two groups, that is, they are about 49% lower in gradient relative to bright-line areas, and the difference is significant at the 5% level (p-value=0.016). This pattern is robust to specification choices.

3.4.2 Change in Arsenic Exposure

Even though we find that less switching happened at higher arsenic levels in gradient villages, it is still possible that conditional on switching from an unsafe well,

households in these villages chose safer alternatives to switchers in bright-line areas. Table 7 contains a summary of "beneficial", "harmful", and "unknown" switches in gradient and bright-lines villages, described in Section 2.3.2. There are more beneficial switches in bright-lines villages, but the percentage of all switches that are beneficial is roughly the same in gradient and bright-lines villages (25% in gradient versus 28% in bright-lines). A Pearson's chi-squared test cannot reject the null hypothesis that there is no difference in switching patterns by intervention (p-value of 0.41). Furthermore, using our estimated changes in arsenic exposure (see Section 2.3.2), the average estimated decrease in arsenic exposure among switchers in gradient villages was 70 ppb and in bright-lines villages the average decrease was 91 ppb. However, this 21 ppb differences is not statistically significant (p-value of 0.44 adjusting for clustering at the village level). We also examine the pattern of switching among moderately unsafe households (50-100 ppb) and very unsafe households. While the percentage of beneficial switches among the very unsafe households in bright-lines villages was slightly higher than among gradient villages (34% versus 30%), this difference is not statistically significant.

To more explicitly estimate the effect of the gradient message on change in arsenic exposure we estimate regression models similar to (1), but with change in arsenic as the dependent variable. Column 1 in Table 8 contains regression results for a model where the change in arsenic level (a positive changes indicate a decrease in arsenic

exposure) is regressed on gradient, (log) arsenic and their interaction. In column 2 we also estimate a specification that includes a full set of control variables and strata dummies. In both specifications the effect of the gradient message is small and not statistically significant. The point estimate for the gradient variable in the full specification is 56 ppb and the p-value is 0.79, while the point estimate of gradient interacted with log of arsenic is -12 with a p-value of 0.78.

While there are many switches for which we do not have precise changes in arsenic exposure, the data we have does not indicate that switching was more or less health-beneficial in gradient villages.

3.5 Interpretations of Observed Behavioral Responses

The results described so far have shown that the more complex gradient message had the desired effect of increasing switching rates relative to the standard bright-lines format only for moderately unsafe levels of arsenic. Among users of very unsafe wells, the simpler bright-lines message appeared to be more effective at promoting switching. This pattern of results survives several specification checks and additional hypotheses tests and is therefore hard to dismiss as purely spurious. In this section we use specifically collected data on arsenic-related knowledge and risk perceptions to test several possible explanations for the pattern of switching responses.

3.5.1 Differences in Risk Perceptions at Baseline

The first hypothesis for these findings is that, immediately after the test results were conveyed, households' understanding or perception of the safety of the well water differs across the distribution of arsenic, as a function of the communication mode. In particular, we examine whether respondents from households in the bright lines group are less likely to recognize their well as unsafe when the arsenic is in the moderately unsafe range, but more likely to do so when the arsenic concentration increases. We do not find much support for this hypothesis. Shortly after communicating the arsenic level, the surveyors asked whether the respondent considered the well's water safe to drink. The results, in Table 9, show several clear patterns. First, a sizeable number of respondents do not appear to understand or believe the information just delivered to them. Of a total of 533 households, only 326 (61%) correctly assessed whether their well was safe or unsafe based on the actual arsenic level we had just given them and the Bangladesh standard of 50 ppb which had also just been presented. Second, the concordance between test results and responses is significantly stronger when we delivered "good news": more than 80% of respondents (=(78+92)/(96+111)) correctly identified their well as "safe" when the result indicated an arsenic level below 50 ppb, while only 48% (=(15+20+63+58)/(52+57+118+99)) immediately recognized the water source as unsafe when the arsenic level is above the threshold. Third, the proportion of

respondents who mistakenly identified unsafe wells as safe is much lower among users of highly unsafe wells (35% of households with As > 100) relative to users of moderately unsafe wells (65% of households with 50 ≤ As ≤ 100). Fourth, conditional on actual safety, the communication mode does not appear to have influenced perceptions much, although among users of unsafe wells, the bright lines message led a slightly lower fraction of wells correctly identified as unsafe relative to the gradient message (46 vs. 50%). However, the difference is small enough that the null hypothesis that the distribution of responses is independent of the communication mode (conditional on actual safety status) is not rejected at standard levels. Finally, the figures in columns 3 and 4 show that the probability of a correct safety assessment is also very similar between experimental groups when we only look at households whose well-arsenic is between 50 and 100 ppb. Thus, the results in Table 6 suggest that the large gap in switching rates between gradient and bright lines messages among users of moderately unsafe wells does not appear to be explained by differences in understanding or perception of well safety immediately following result delivery.

Similarly, the communication mode had only a marginal impact on the self-reported likelihood of a switch to a safer source of drinking water within a year (not reported in the table). The likelihoods were recorded immediately after the question about the perceived safety status of the well, by asking the respondent "in your opinion,

how likely are you to switch to a safer source of drinking water over [the next year]?" Perceived probabilities were elicited using physical objects as described in Section 2.3. Among households with a moderately unsafe well, the mean perceived probability of moving to a safer well was only 15 and 18% for the gradient and the bright lines communication mode, respectively.[15] As a reminder, these figures considerably underestimate the actual switching rate among households in the gradient group (35%), while they are close to the actual figure for the bright lines group (23%). The perceived likelihood of switching remains very low when we look at households exposed to water with As > 100 ppb, for which the figures are 15% and 21% for gradient and bright lines, respectively. Note also that, at these latter exposure levels, the immediate stated intentions do reflect the reality, documented at follow-up, that a smaller fraction of households changed source among those who received the gradient message.

3.5.2 Differences in Risk Perceptions at Follow-up

In reality, it is likely that the immediate respondent's reactions to the provision of information is only a noisy representation of all the elements taken into account by households when making decisions about where to fetch drinking water. The test results are likely to be discussed with other members (especially the male head), and both

[15] Similar questions were also asked with a 1, 3 and 6-month horizon. As expected, predicted switching rates were even lower at these shorter time intervals.

comprehension and risk perceptions are likely to change as a consequence. For this reason, we next consider knowledge and perception data collected during the follow-up survey, completed 7-9 months later. A first notable observation is that, despite the information provision, more than 90% of respondents still do not know the exact threshold for safety (row A in Table 10), regardless of actual well safety status or communication mode. Indeed among the 533 panel households, 480 respondents literally said they did not know the threshold, while only 23 recognize the correct figure. Separate questions then asked how the respondent would choose where to drink if given the choice of two wells both labeled "unsafe" (row B) or "safe" (row C). Overall, we find that the gradient message, against our expectations, did not lead to better decision making: for users of both moderately and highly unsafe water, a higher fraction of respondents incorrectly stated that it makes no difference, because all (us)safe well are equally (un)safe, although the differences are not statistically significant. As an aside, note also that indifference is expressed more frequently in the choice between two safe wells (about 60-70% of cases, row C) than in the choice of wells with As > 50ppb (about 40-50%, row B). Taken together, the findings in rows A to C provide some mild evidence in favor of the hypothesis that the more complex gradient message "confused" people leading to worse choices.

Next, additional and more pertinent information is provided by direct questions about the perceived safety of the tested water (row D). Almost all respondents recognize correctly the "safe" status of wells whose water indicated arsenic concentrations below 50ppb. However, a large number of respondents incorrectly identified as safe water from wells above the threshold. Consistent with the higher switching rates among users of moderately unsafe water who received the gradient message, we find that the unsafe status is correctly identified by 60% of respondents, while this happens in only 44% of the cases in the bright lines group. The difference is significant at the 10% level (p-value= 0.074). This result is perhaps not surprising, given that, without the emphasis on the gradient, users of moderately unsafe wells may be led to think that their water source is close enough to be safe that no mitigation is necessary. Again consistently with the patterns apparent from Figure 9 (see also row E in Table 10), the fraction of respondents who correctly identify the unsafe status among users of highly unsafe wells is instead lower when the gradient message was used, although the difference in this case is very small (70 vs. 76%) and not significant.

Overall, perceptions about safety status measured at follow-up are then broadly consistent with the unexpected switching patterns we have described. An important caveat, however, is that we cannot exclude that such consistency can be at least partly ascribed to ex-post rationalization. That is, some respondents may state or actually

convince themselves that an unsafe well does not pose a health risk as a way to justify the choice to keep using it. On the other hand, if at all present, such ex-post rationalization was not a universal phenomenon. In fact, we find that among the 215 households who were still using an unsafe well at follow-up, 133 (62%) recognized that the well water was unsafe to drink. The proportion is almost identical between the two arms: 64% with bright lines and 60% with gradient.

3.5.3 Discouragement

Another possibility is that inactivity among users of highly unsafe wells is due to discouragement: the emphasis on the gradient may have induced some of these users to believe that past exposure had already been so heavy to make a switch to a safer source pointless, despite the explicit suggestion to move contained in the gradient message.[16] However, such hypothesis is largely inconsistent with the figures in Table 10. First, respondents in the gradient group are actually less likely to recognize that the choice between two unsafe wells is a choice of consequence for their health (row B, columns 5 and 6). Second, as we have mentioned, such respondents are also less likely to recognize the water as unsafe, although the difference relative to bright lines is very small. Finally, information on the reasons for not switching to a safer source collected at follow-up is

[16] The few existing medical studies show that all-cause mortality and certain cancer risks may take decades to decline after exposure to arsenic has dropped, Chang et al. 2004, Yang et al. 2005, Argos et al. 2010.

also not consistent with this hypothesis. A majority of the 137 users of highly unsafe wells justified the choice not to switch on grounds of safety perceptions and distance, and not on the basis of other concerns. The proportion is indeed even higher (68%) in the gradient relative to the bright lines group (58%). Although our data do not separately indicate whether "other" included responses such as "it is too late for risk mitigation", these results overall do not support discouragement as a compelling explanation for the lower switching rates among users of highly unsafe wells in the gradient group.

3.6 Conclusions and Discussion

The cluster randomized controlled trial described in this paper was designed to test if providing households with more detailed information on the gradient between arsenic exposure and arsenic risk could induce more households to switch well sources than the standard bright-lines "safe/unsafe" risk presentation. We find evidence of this effect only for households using moderately unsafe wells (arsenic between 50 and 100 ppb), where the observed switching rates are 50% higher (35 vs. 23%) in areas where the gradient communication mode was used relative to bright-line communities. However, for users of wells with higher arsenic concentrations (where the bulk of the arsenic distribution is, encompassing mean and median), the effect of the gradient message is to decrease switching. For wells with arsenic levels above 100 ppb the fraction of users moving to an alternative source is 40% lower (28 vs. 47%) in areas where we used the

gradient relative to locations where the standard bright-line message was adopted. This latter difference is statistically significant at the five percent level.

Even though there was less switching in gradient villages, it could still be the case that the switching that did happen lead to greater reductions in arsenic exposure. We examined whether there were any differences in the estimated level of arsenic exposure reduction and found no evidence that switching in gradient villages resulted in greater reductions in arsenic exposure relative to switching in bright-lines villages.

The pattern of switching behavior is remarkably consistent and robust to specification checks. While we cannot fully explain the pattern, it is broadly consistent with data collected on perceptions of risk from arsenic. Immediately following provision of results, there is no statistical difference in risk perceptions among the bright lines or gradient groups for users safe, moderately unsafe, or very unsafe wells. By the follow-up survey, seven to nine months later, differences in risk perceptions had developed. In particularly, gradient households in the moderately unsafe range were more likely to perceive that the water from their well was unsafe compared to households with similar arsenic levels who received the bright lines message. Among users of very unsafe wells this pattern was reversed (but not statistically significant). While some of this change in risk perceptions could be ex-post rationalization, we offer evidence that this does not explain all of the differences in perception. Taken together

these results suggest that conveying information about the continuous nature of arsenic risk may not lead to increases in health-improving behaviors and may actually have the opposite effect for the most at-risk population, at least in the short-term (less than one year).

There are three important caveats for our findings. First, the bright-lines safe/unsafe message is prevalent throughout Bangladesh and certainly households in Araihazar had been accustomed to hearing information about arsenic in the safe/unsafe format. While our findings that the gradient message did not result in greater rates of health-improving behavior among the most exposed households, may well hold for Bangladesh, it may not hold in other settings where the bright-lines message is not already dominant.

Second, our intervention was limited in scope. Presentation of the gradient in arsenic risk was limited to oral information given to respondents when the test results were displayed. The test result plates themselves focus largely on the safe/unsafe message and these plates were the same in both gradient and bright-lines households. A more sophisticated presentation of the gradient in risk, perhaps gradients of colors or a bar that represents the level of arsenic in the well relative to others in the village, may have greater impacts.

Third we examine switching choices over a relatively short time horizon. The time between our baseline and follow-up surveys was less than one year. In other work (Soumya et al. 2010) we find that switching away from unsafe wells does not always happen in the short-term after results are provided. Soumya et al. (2010) find significant numbers of households that switch off unsafe wells more than two years after they are first informed that they are using an unsafe well. The effect of gradient information may take time to have an impact.

Our results are consistent with previous work on health labeling and risk communication which has found that these information-based programs may be least effective among higher risk individuals. Our intervention was successful at inducing a large relative increase in switching from unsafe wells among users of moderately unsafe sources, but the opposite was true for higher exposure. Given the vast magnitude of the arsenic contamination problem in Bangladesh, as well as in other parts of the world, further research is clearly needed in order to develop more effective health risk communication strategies.

Table 4: Baseline summary statistics and randomization tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Diff. b/w experimental arms (Gradient-Bright-line)*					
					All		Moderately unsafe <=50As<=100		Highly unsafe As>100	
	Obs	Mean	Median	Std Dev	Mean	p-value	Mean	p-value	Mean	p-value
Well Arsenic Level	533	116	80	149	17	0.6	-4.9	*.063	79	**.029
As >50 ppb	533	0.61	1	0.49	-0.06	0.62	N/A	N/A	N/A	N/A
# Household members	533	5.3	5	2.5	0.09	0.75	-0.12	0.82	-0.11	0.77
Household head: age	525	46	45	14	0.25	0.88	1.2	0.64	1.8	0.36
Household head: Can read/write	521	0.39	0	0.49	-0.02	0.62	-0.12	*.096	0	0.99
Household head: secondary education or above	515	0.21	0	0.41	-0.02	0.74	-0.091	0.2	-0.043	0.46
Household head: woman	525	0.19	0	0.39	-0.05	0.15	-0.1	0.12	0.012	0.8
Number of adult females	533	1.7	1	0.89	-0.11	0.25	-0.22	*.088	0.012	0.94
Number of children	533	3.1	3	1.6	-0.05	0.78	-0.035	0.91	0.1	0.7
% members age >10 who can read/write	533	0.55	0.5	0.33	-0.02	0.68	-0.043	0.42	-0.016	0.75
% of 6-14 in a household in school	375	0.76	1	0.36	-0.02	0.61	-0.12	**.019	-0.035	0.64
Well Network size	533	1.3	1	1.5	-0.12	0.45	-0.82	***.002	0.21	0.4
Value of food consumed: monthly	530	5073	4333	3339	507	*0.07	32	0.94	262	0.48
Total expenditure: monthly	527	5942	5000	3227	371	0.16	129	0.81	378	0.34
Typical income: monthly	495	7672	6000	7193	515	0.4	331	0.73	1132	0.3

Table 4 cont: Baseline summary statistics and randomization tests

					All		Moderately unsafe		Highly unsafe	
	Obs	Mean	Median	Std Dev	Mean	p-value	Mean	p-value	Mean	p-value
Expenditure on medicines: monthly	510	543	250	1227	-159	0.13	-38	0.66	-240	**.037
Uses sanitary latrine	533	0.8	1	0.4	0	0.98	0.14	*.081	0.022	0.73
Pakka house/ walls (good quality)	533	0.11	0	0.31	-0.01	0.83	0.03	0.55	-0.063	0.26
% members with symptoms of arsenic poisoning	533	0.01	0	0.07	0	0.69	-0.0032	0.3	0.014	0.32
Any member with symptoms of arsenic poisoning	533	0.04	0	0.19	0.02	0.56	-0.019	0.3	0.059	0.25
Mean # days of illness last year (ages 6 to 70)	532	19	13	22	-0.23	0.91	4.4	0.33	-3.1	0.29
Household owns well	527	0.7	1	0.46	-0.019	0.6	0.045	0.54	-0.075	0.18
Distance to nearest well below 50 ppb	529	75	21	219	55	0.4	-13	0.62	166	0.22
Distance to nearest safer well	531	86	47	137	-8.1	0.58	-49	0.13	12	0.55
Average concern about short-term arsenic risk	513	1.2	1	0.74	0.087	0.35	0.24	0.14	0.052	0.74
Average concern about long-term arsenic risk	510	7.8	8	1.6	0.098	0.64	0.52	0.13	-0.077	0.81

* Figures in columns 5, 6 and 7 show the mean difference between treatment groups for the whole sample and respectively for moderately and highly unsafe wells. Figures in columns 6,8 and 10 show p-value for test of equality of means for the relevant sample. Tests are robust to intra-cluster correlation of residuals. Asterisks indicate significance at the 1 (***), 5(**) or 10(*) percent level.

Table 5: Tubewell arsenic alevels and household characteristics

	(1) Unsafe (As>50)	(2) Arsenic Level
# Household members	0.019	0.525
	[0.017]	[3.636]
Household head: age	-0.001	-1.05
	[0.002]	[0.411]*
Household head: can read/write	0.076	8.814
	[0.062]	[22.931]
Household head: secondary education or above	-0.1	-51.431
	[0.075]	[31.670]
Household head: woman	0.004	-27.147
	[0.068]	[19.700]
Number of adult females	0.003	2.055
	[0.040]	[10.157]
Number of children	0.01	3.277
	[0.035]	[11.517]
% members age> 10 who read/write	0.003	20.276
	[0.093]	[31.023]
Network size	-0.021	7.902
	[0.017]	[7.130]
Value of food consumed: monthly (1,000s)	-0.015	-1.837
	[0.005]**	[1.161]
Total expenditure: monthly (1,000s)	-0.004	0.105
	[0.009]	[2.754]
Uses sanitary latrine	0.06	-1.563
	[0.065]	[15.986]
Pakka house or pakka walls (good quality)	0.011	2.667
	[0.072]	[18.373]
Mean # days of illness last year (age 6 to 70)	0	-0.062
	[0.001]	[0.215]
Average short-term concern for arsenic risk	-0.041	-3.341
	[0.042]	[10.461]
Average long-term concern about arsenic risk	0.031	0.36
	[0.021]	[6.740]
Constant	0.402	154.15
	[0.219]	[69.875]*
Observations	481	481
R-squared	0.03	0.03
# clusters	42	42
F-test of regression	1.91	1.81
p-value	0.049	0.064

Source: Authors' calculations from baseline survey (Spring 2008). Standard errors in brackets are robust to intra-cluster correlation. Asterisks indicate significance at the 1 (***), 5(**) or 10(*) percent level.

Table 6: Effect of communication mode on switching decisions

Dependent variable: SWITCH	(1)	(2)	(3)	(4)
Gradient	1.429	1.245	1.164	1.021
	[0.361]**	[0.412]**	[0.392]**	[0.332]**
ln(Arsenic)	0.267	0.242	-0.035	-0.177
	[0.050]**	[0.045]**	[0.307]	[0.296]
ln(Arsenic) *Gradient	-0.306	-0.268	-0.251	-0.217
	[0.069]**	[0.082]**	[0.077]**	[0.067]**
# Household members		0.032	0.039	0.03
		[0.018]	[0.019]*	[0.021]
Household head: age		0.002	0.001	0.001
		[0.002]	[0.002]	[0.002]
Household head: Can read/write		0.148	0.158	0.15
		[0.091]	[0.085]	[0.084]
Household head: secondary education or above		-0.252	-0.283	-0.27
		[0.084]**	[0.087]**	[0.086]**
Household head: woman		0.025	-0.013	-0.017
		[0.068]	[0.060]	[0.058]
Number of adult females		-0.078	-0.069	-0.101
		[0.058]	[0.061]	[0.062]
Number of children		-0.017	-0.028	-0.013
		[0.032]	[0.036]	[0.040]
% members age>10 who read/write		-0.066	-0.066	-0.069
		[0.124]	[0.114]	[0.104]
Network size		0.001	0.005	0.007
		[0.023]	[0.023]	[0.021]
Value of food consumed: monthly (1,000s)		0.018	-0.005	0.007
		[0.022]	[0.023]	[0.020]
Total expenditure: monthly (1,000s)		-0.013	-0.005	-0.006
		[0.017]	[0.017]	[0.016]
Uses sanitary latrine		-0.145	-0.185	-0.162
		[0.064]*	[0.070]*	[0.068]*
Pakka house or pakka walls (good quality)		-0.08	-0.037	-0.055
		[0.114]	[0.118]	[0.119]
Mean # days of illness last year (age 6 to 70)		0.001	0.001	0.001
		[0.001]	[0.001]	[0.001]
Owns well		0.062	0.042	0.034
		[0.058]	[0.056]	[0.054]
Distance to nearest safe well		0	0	0
		[0.000]	[0.000]	[0.000]

Table 6 cont: Effect of communication mode on switching

Dependent variable: SWITCH	(1)	(2)	(3)	(4)
Average short-term concern for arsenic risk			0.311	0.321
			[0.421]	[0.442]
Average short-term concern *ln(Arsenic)			-0.042	-0.052
			[0.086]	[0.090]
Average long-term concern about arsenic risk			-0.218	-0.3
			[0.246]	[0.246]
Average long-term concern*ln(Arsenic)			0.04	0.058
			[0.049]	[0.048]
Constant	-0.926	-0.809	0.716	1.18
	[0.251]**	[0.296]**	[1.541]	[1.505]
Stratum dummies included				y
Observations	326	308	297	297
R-squared	0.05	0.13	0.15	0.22
Number of clusters (villages)	42	41	41	41

Source: Authors' calculations from Wave I and Wave II data. All estimates are Linear Probability Models where the dependent variable equals 1 if the household switched to a different drinking source after communication of test results. Standard errors in brackets are robust to intra-cluster correlation. Asterisks indicate significance at the 1 (***), 5(**) or 10(*) percent level.

Table 7: Beneficial and harmful switches by intervention and arsenic level

		As<50 (safe)		50<=As<=100 (moderately unsafe)		As>100 (highly unsafe)	
		Bright Line	Gradient	Bright Line	Gradient	Bright Line	Gradient
Beneficial	obs	0	0	3	5	18	8
	%	0	0	25	26.32	33.96	29.63
Harmful	obs	2	2	0	1	0	1
	%	2.22	40	0	5.26	0	3.7
Unknown	obs	7	3	9	12	35	18
	%	77.78	60	75	68.42	66.04	66.67

Source: Authors' calculations from Wave II survey. Well switching is classified as beneficial if the household moved to a well with a lower level of arsenic or from a red well to a green well. Switching is classified as harmful if the household switched to a well with higher arsenic or from a green well to red well. Unknown switches include switches for which we do not know anything about the arsenic content of the new well and switches from red well to a new red well or from a green well to a new green well

Table 8: Effect of communication mode on estimated reduction in arsenic exposure among switchers

Dependent variable: Estimated change in As	(1)	(2)
Gradient	105.531	55.883
	[194.595]	[209.624]
ln(Arsenic)	175.374	27.773
	[25.063]**	[121.664]
ln(Arsenic) *Gradient	-20.828	-12.203
	[40.166]	[42.629]
# Household members		-3.385
		[5.820]
Household head: age		0.273
		[0.921]
Household head: Can read/write		-22.285
		[19.737]
Household head: secondary education or above		38.478
		[25.910]
Household head: woman		-22.174
		[30.654]
Number of adult females		-1.661
		[12.883]
Number of children		-7.94
		[9.183]
% members age>10 who read/write		21.461
		[37.634]
Network size		-0.845
		[6.012]
Value of food consumed: monthly (1,000s)		3.549
		[11.150]
Total expenditure: monthly (1,000s)		3.781
		[7.819]
Uses sanitary latrine		-35.581
		[21.793]
Pakka house or pakka walls (good quality)		28.072
		[33.769]
Mean # days of illness last year (age 6 to 70)		-0.603
		[0.204]**
Owns well		-39.774
		[14.126]**
Distance to nearest safe well		0.026
		[0.037]

Table 8 cont: Effect of communication mode on estimated reduction in arsenic exposure among switchers

Dependent variable: Estimated change in As	(1)	(2)
Average short-term concern for arsenic risk		149.04
		[179.169]
Average short-term concern *ln(Arsenic)		-25.317
		[35.642]
Average long-term concern about arsenic risk		-118.906
		[100.774]
Average long-term concern*ln(Arsenic)		22.829
		[20.376]
Constant	-786.873	54.211
	[121.364]**	[561.401]
Stratum dummies included	No	Yes
Observations	111	103
R-squared	0.57	0.69
Number of clusters (villages)	34	34

Source: Authors' calculations from wave I and Wave II data. All estimates are obtained with OLS, including only households who switched from an unsafe well, and the dependent variable is the reduction in arsenic exposure estimated as described in section 2.3.2. Standard errors are robust to intra-cluster correlation. Asterisks indicate significance at the 1 (***), 5 (**) and 10(*) percent level.

Table 9: Immediate perceived safety of tested well

		As<50ppb (safe)		50<=As<=100ppb (moderately unsafe)		As>100ppb (highly unsafe)		All	
Is your well's water safe to drink?		(1) Binary	(2) Gradient	(3) Binary	(4) Gradient	(5) Binary	(6) Gradient	(7) Binary	(8) Gradient
Don't know	obs.	10	12	2	1	9	11	21	24
	%	10.42	10.81	3.85	1.75	7.63	11.11	7.89	8.99
No	obs.	8	7	15	20	63	58	86	85
	%	8.33	6.31	28.85	35.09	53.39	58.59	32.33	31.84
Yes	obs.	78	92	35	36	46	30	159	158
	%	81.25	82.88	67.31	63.16	38.98	30.3	59.77	59.18
Total	obs.	96	111	52	57	118	99	266	267
	%	100	100	100	100	100	100	100	100
H0: Binary=Gradient (p-values)		0.9232		0.6925		0.5003		0.9248	

Source: Authors' calculations from Wave I survey. The figures show the responses to the question "[d]o you consider the water from your tubewell to be safe to drink?", asked shortly after the delivery of the test results.

Table 10: Perceived safety of tested well at follow-up

			As<50ppb (safe)		50<=As<=100ppb (moderately unsafe)		As>100ppb (highly unsafe)	
			(1) Binary	(2) Gradient	(3) Binary	(4) Gradient	(5) Binary	(6) Gradient
(A)	Does not know 50ppb threshold	%	0.95	0.96	0.98	0.95	0.97	0.93
(B)	Thinks all ``unsafe'' wells the same	%	0.44	0.38	0.4	0.54	0.42	0.53
(C	Thinks all ``safe'' wells the same	%	0.53	0.64	0.6	0.67	0.58	0.74
		%						
(D)	Tested well water is unsafe to drink	%	0.04	0	0.44	0.6	0.76	0.7
(E)	Switched to a different source	%	0.094	0.045	0.23	0.33	0.45	0.27
(F)	P(health risk within 1m/5y)		0.03	0.018	0.099	0.13	0.15	0.16
(G)	P(health risk within 10/20 years)		0.12	0.078	0.3	0.4	0.43	0.47

Source: Authors' calculations from Wave II survey. N=533

A: % respondents who do not recognize that the Government of Bangladesh considers water with As>50 ppb unsafe to drink

B and C: % respondents who, if given a choice between two unsafe (B) or safe (C) well, state that it does not matter which one is chosen as source of drinking water

D: % respondents who think that the well water tested at baseline is unsafe to drink.

E: % households who switched to a different source between baseline and followup

F: mean of six household-specific average subjective probabilities of developing health conditions in the short-term as a consequence of drinking the tested water (risk of skin lesions within 1 month and within 1 and 5 years and risk of "serious health conditions" within the same time-frames)

G: mean of four household-specific average subjective probabilities of developing health conditions in the long-term as a consequence of drinking the tested water (risk of skin lesions within 10 or 20 years and risk of "serious health conditions" within the same time-frames)

4. Risk Avoidance Behavior and Social Learning: Does Proximity to Neighbors Matter?

4.1 Introduction

Tube-well testing and labeling has been the most important policy-response to the arsenic crisis in Bangladesh. The World-Bank sponsored Bangladesh Arsenic Mitigation Water Supply Project (BAMWSP) tested 5 million tube-wells across the country and painted wells containing arsenic more than 50 ppb red, and those below 50 ppb green. The information provided through such programs enables households to understand whether their current well is safe for drinking, and also gives households information on the availability of safe alternative sources that they can potentially switch to. Households, however, likely also need information about the costs and benefits of source-switching.

There are costs of sharing tube-wells for both "borrowers" and owners of safe tubewells. Costs to borrowers include the cost of searching for a suitable source and the inconvenience of walking further for fetching water (Madajewicz et al. 2007), as well as the feeling of being socially obligated to the owner (Schoenfeld 2005). Owners have concerns about quicker wear-and-tear of the hand-pump due to more users, and the loss of privacy due to non-household members visiting their well (Hanchett et al. 2002). This suggests that households may have to learn about these costs by experimenting with source-switching themselves, or learn about these costs from their relatives, friends and neighbors. On the other hand, households may better understand the importance of

avoiding exposure to arsenic by speaking with their friends and neighbors, or by observing them switching sources. The BAMWSP project also incorporated a message that was delivered through television, radio and newspapers and provided factual information to households across the country about the arsenic problem and the diseases associated with drinking arsenic-contaminated water (Caldwell et al. 2005; Madajewicz et al. 2007). This media campaign drew attention to the damages that could be avoided by switching away from unsafe sources—the benefits of source-switching.[1]

In Chapter 2, the source-switching behavior of households in Araihazar tested by BAMWSP over two time periods was examined. The results indicated that source-switching diffused over tine—households that had not switched sources within two years of testing switched sources between two and five years of switching, almost doubling the short-term switching rate. Households were asked to self-report their reasons for this late-switching behavior. The most-frequently reported reason was that these households had better understood the dangers of arsenic contamination over time by talking to neighbors and relatives (34%). Twenty-three percent of households also reported that they had become more aware of the dangers of arsenic contamination after 2005. The third reported reason was that these households had observed other households switching to new sources (14%). These self-reported reasons suggest that

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[1] Our interviews suggest that households are aware that drinking arsenic-contaminated water increases the chances of contracting skin-lesions and developing serious health problems. Both these health-problems were emphasized through the media campaign.

provision of health-risk information through a campaign may not lead to immediate avertive action by many households. Information about the benefits and costs of source-switching acquired by observing and interacting with relatives and friends—social-learning—may play an important role in the uptake of arsenic-safe water sources. This leads us to consider the role of social-learning in the context of source-switching.

The basic idea behind the question of social-learning is whether the behavior of an individual is determined by the behavior of the group that individual is a part of. However, identifying the effect of group-behavior on individual behavior is challenging. This is because not only is group behavior itself determined by the behavior of individuals that comprise that group; individuals belonging to the same group are likely to be similar in ways that are unobservable, and often time-invariant. This is referred to as the "reflection" problem (Manski 1993), and confounds the identification of the effect of group behavior on individual behavior.[2]

The identification of this relationship between group and individual behavior has been pioneered through the modeling of the diffusion of new technology in agriculture. This literature has dealt primarily with identifying the effect of social learning in technology-diffusion *after* a technology had been adopted (Bandiera & Rasul

[2] In his seminal paper, Manski (1993) notes that a linear relationship between individual and group behavior during the same period often does not permit identification of the effect of group-behavior on individual behavior, thus calling for sophisticated techniques.

2006).[3] Farmers take decisions simultaneously, and choices of other farmers are observed in the next period (Conley & Udry 2001). An individual farmer's input-decision is modeled as a function of her beliefs about the output it would produce, which are influenced in the next period by her *observations* of other farmers' input decisions and output realizations from the current period (Foster and Rosenzweig 1995; Conley & Udry 2001; Munshi 2004). Farmers in a village are typically mapped to all other farmers, though recent studies have demonstrated the importance of identifying the exact network a farmer in a village belongs to (Bandiera & Rasul 2006; Conley & Udry 2010).

A recent, but growing, body of literature examines whether attitudes towards and adoption of new health-related behaviors are affected by the attitudes and actions of peers, by drawing upon the social-learning literature in agriculture. Much of this recent work involves randomized experiments to control for unobserved similarities within group members that may drive similar behavior; collection of behavioral data at multiple time-periods (panel data); identification of direct interconnections between decisions-makers by explicitly asking questions about interactions; and identification of specific time-periods the behavior in question was adopted to identify early and late

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[3] Bandiera & Rasul (2006) model the *initial* adoption of sunflower cultivation, where a farmer's beliefs about the optimal input level to produce a certain output are determined by the number of neighboring farmers the farmer in question knows are also planting sunflower crop. Thus a unique reference group per farmer is identified.

adopters (Behrman et al. 2001; Miguel and Kremer 2004; Munshi and Myaux 2006; Oster & Thornton 2009). The peer group, as suggested by the empirical evidence in the agriculture and health literature, may be based on proximity, gender, age, religion and kinship (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Munshi & Mayux 2006; Conley and Udry 2010).[4]

In this chapter I examine whether a household's tubewell switching-decision is affected by the switching decisions of its proximate neighbors. The majority of households in the data switched sources only once, but we have information about the time period the household switched. I address the problem of simultaneity between individual actions and neighbors' actions by identifying households that switched tube-wells early, later or never. I use this information to examine whether early-switching decisions affect late-switching decisions (Manski 1993). This helps address the reflection problem because an early-switching household cannot be affected by the behavior of a late-switching household. However, households can still behave like their neighbors due to unobservable similarities. Due to a lack of panel data, I pursue an instrumental-variable strategy to address this problem. This enables the identification of neighbors'

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[4] Some methods for examining whether individual behavior varies by group behavior do not require agents to observe each others' actions. Bajari et al. (2006) examine a static game of incomplete information, where an individual's decision to take an action varies with her expectation of how others in the group will behave. Agents are making decisions simultaneously and hence do not observe each other's actions or outcomes; these expectations are formed by each agent for every other agent, based on the characteristics she observes other agents to have, and which are unique to those agents. Such a method is particularly useful while examining decisions that produce externalities that are also enjoyed by agents who decide to not take such decisions (free riders).

behavior attributable only to factors that are specific to them, and not due to similarities between the household and the neighbors. The results suggest that while a household is more likely to switch when a greater fraction of its proximate neighbors switch sources, identifying a causal relationship between neighbors' and household behavior is challenging.

I proceed in the following manner. Section 4.2 describes the data. Methods are described in section 4.3. In section 4.4, results are presented and in section 4.5, implications for future work are discussed.

4.2 Data

The data for this chapter come from a 100km2 area of Araihazar district in Bangladesh. Data were originally collected by Schoenfeld (2005) from sixty-two villages, covering the population of tube-wells in the area. Further data was collected from a sample of these households in 2008.

The villages were selected by Schoenfeld (2005). From a database of 30,000 well tests provided by BAMWSP in 2003, eight villages were chosen with a mixed distribution of safe and unsafe wells (50/50), and eight villages were chosen for having a particularly high proportion (80–100 %) of unsafe wells. As additional funding became available, 46 more villages with medium to high proportions of unsafe wells were chosen from the dataset. The purpose of Schoenfeld's study was to document source-switching during 2003-05 in response to BAMWSP testing in 2003. The well owner's

wife, or a close female relative, was asked a standard set of questions by trained field-workers. The field- workers also noted the Global Positioning System (GPS) coordinates of the well, and whether the well had any color visible on it. For the remainder of the chapter, we refer to the households that were tested and delivered results by BAMWSP in 2003 as Group-A households.

At the time this study was being conducted, Schoenfeld's team came across 533 tube-wells in 48 villages that had been installed after BAMWSP had conducted arsenic testing in these villages. Samples of water were collected from these tube-wells for arsenic-testing[5], and these households received results in 2008. We refer to the households that received results in 2008 as Group-B households for the reminder of the paper. In the data, a household either belongs to Group-A or Group-B, but never to both (Figure 11).

[5] The remaining nineteen villages did not have untested/newly installed wells.

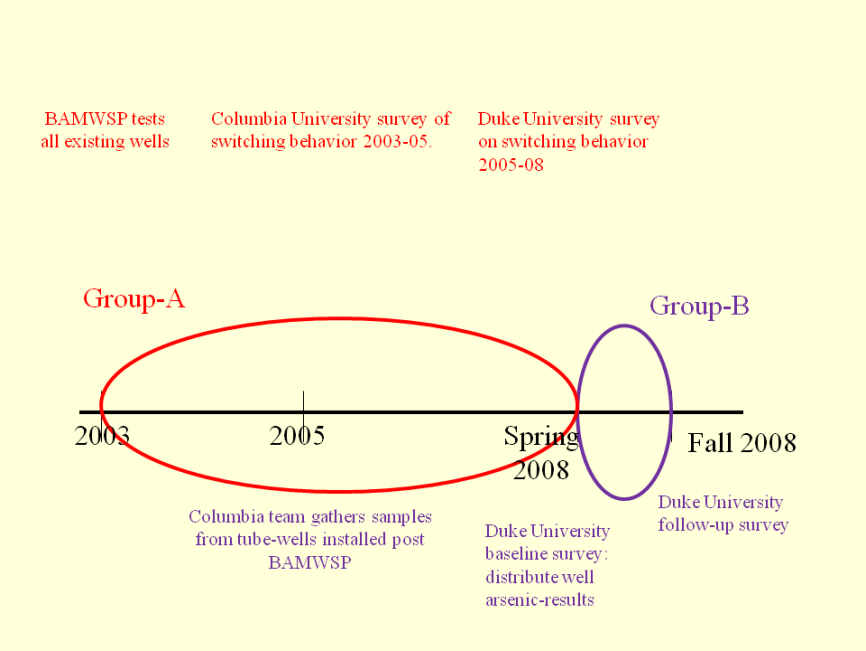

Figure 11: Data collection timelines

Additional data from both Group-A and Group-B households was collected in 2008. During Spring 2008 (January-April), data on switching behavior during 2005-08 was collected from Group-A households. At the same time arsenic results were distributed to Group-B households and a baseline survey was also administered to these households. During Fall 2008 (October-November), A follow-up study was administered to Group-B households and data on their switching behavior during a six-month period between baseline and follow-up was collected. The survey instruments for Group-A and Group-B households were separate; however questions eliciting socioeconomic information were identical in both surveys. Questionnaires for both groups of households were translated into Bangla by the same individuals, in order to minimize

bias in translation. The survey instruments were pre-tested in 2 of the 62 villages containing both Group-A and Group-B households. Data from these villages are not used in the analysis.

For Group-A households, switching behavior during 2005-08 was recorded in 59 of the 60 villages.[6] The questionnaire could not be administered to all Group-A households in each village due to time and resource constraints. A random number was generated for each tube-well in the village, and interviews were conducted in ascending order of random numbers. In each household, the female responsible for making decisions about water sources was interviewed. This provided a random sub-sample of 1557 Group-A households in 59 villages.

For Group-B households, delivery of arsenic results and administration of the baseline study were conducted simultaneously while interviewing Group-A households, and a follow-up survey of switching behavior was administered six months later. After piloting, Group-B tube-wells were distributed across 46 villages; one village was not visited because it only included a single tested well, two villages were visited at baseline but not at follow-up, because each village had a single well that was no longer in use by 2008. Hence, overall the Group-B households are spread across a total of 43 villages. At the baseline study, we were able to locate 434 tube-wells in 43 villages in their original location (the tube-well was found to be located at the same GPS coordinates as recorded

[6] An additional village could not be visited due to time constraints.

when samples of water were collected in 2005). Results were displayed on these tubewells. The baseline survey was administered to 668 Group-B households using these tubewells during the baseline study, of which 596 households were using these tube-wells as their primary drinking-water source at the time of baseline survey. The follow-up survey was completed for 533 of those 596 Group-B households. Thus, the Group-B sample is a balanced panel of 533 households that completed the baseline and follow-up surveys and who were using the tested well as the primary source of drinking water when the baseline survey was administered in Spring 2008.[7, 8]

Table 11 displays summary statistics for Group-A and Group-B households. I focus on the comparison between Group-A and Group-B households to understand whether there are any systematic differences between the two kinds. Households in Group-B are making switching decisions after observing neighbors for a longer time than households in Group-A. There may also be differences in characteristics between the two groups that influence switching behavior. These characteristics were recorded at the time the household was interviewed (during spring 2008). Group-B households appear to have lower monthly expenditures on food (by 410 BDT). Respondents in

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[7] As demonstrated by previous work, the most important reason for switching sources is arsenic. We therefore restrict ourselves to examining Group-B households that were drinking water from the well order to know the arsenic status of the primary drinking-water source at the start of the study.

[8] Group-B households were randomly assigned (at the village level) to receive one of two different messages regarding arsenic in their drinking water (chapter 3). I therefore take this treatment into account while examining the effect of neighbors on Group-B households' switching decisions. The effects of neighbors' actions on a household's switching decision do not change when treatment is not taken into account; therefore I do not report the results of the treatment. While examining the effects of neighbors' actions on Group-B households, results are adjusted for clustering at the village level.

Group-B are younger and a lower fraction of them can read and write Bangla, in contrast to their counterparts in Group-A. Group-B families are also smaller, and have more children per household than in Group-A. Fewer Group-B households report arsenic symptoms in their household than in Group-A. In contrast to Group A, a smaller fraction of members per Group-B households has completed primary and secondary education. They also appear to be less connected with neighbors and friends within their villages, with Group-B households knowing fewer people with arsenic symptoms, and discussing arsenic with fewer neighbors, friends and relatives than Group-A households.

4.2.1 Constructing Networks

Using GIS, I calculate the fraction of safe wells within 300 meters for Group-A and Group-B households by using geo-codes of the population of tubewells in the village (collected by Schoenfeld's study). [9] I also calculate Euclidian distances between every pair of tube-wells, in meters. Following Conley and Udry (2010), I used these distances to construct rings of progressively further neighbors for each household, to identify sets of neighbors based on geographical proximity.

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[9] The self-reported average walking time is 2.75 minute, and 83 % of households spend two minutes or less, walking to their water source. Assuming that one can walk 5000 meters in 60 minutes, households walk about 250 meters to fetch water. We construct the set of alternative water sources to be wells within 300 meters of the household's present well. This data helps us control for the alternative sources a household can switch to.

In the first case, I first map Group-A households to Group-A neighbors. Two periods of switching behavior are observed for each Group-A household—behavior during 2003-05 and during 2005-08. This allows me to examine whether the switching decisions of neighbors during 2003-05 affect the switching decisions during 2005-08 of those households that did not switch during 2003-05. In the second case, I map Group-B households to Group-A neighbors and examine whether Group-B households' decisions to during Jan-Nov 2008 are affected by the actions of Group-A neighbors taken any time from 2003 to January 2008.

Table 12 displays summary statistics for the fraction of neighbors within 100 meters, 200 meters, 300 meters, 400 meters, 500 meters , beyond 500 meters and all neighbors that were tested unsafe and that switched sources, for Group-A and Group-B households. Within each of the cases, the fraction of neighbors that switch, and the fraction of neighbors that are tested unsafe, are similar across rings of neighbors. Between the two cases, the fraction of neighbors tested unsafe is similar by ring; however, Group-B households have almost twice as many neighbors that switched than Group-A households.

4.3 Methods and Estimation

I use the following equation to examine the effect of neighbors' actions on a household's switching decision.

$$S^{G}_{h,v,t} = \alpha_0 + \alpha_U U^{G}_{h,v,t} + \alpha_C C^{G}_{h,v,t} + \alpha_S Safe^{<300}_{h,v,t} + \alpha_{neis} S^{d,J}_{-h,v,t-1} + \alpha_X X^{G}_{h,v,t} + \nu^{G}_{h,v,t} \qquad (1)$$

Here $S^{G}_{h,v,t}$ refers to the switching decision of household h belonging to Group G in village v in time t; $U^{G}_{h,v,t}$ is the well-arsenic result of the tubewell the household switched away from, and takes a value of one if the tubewell contained above 50 ppb of arsenic; $C^{G}_{h,v,t}$ is the distance to closest safe well from household h; $Safe^{<300}_{h,v,t}$ is the fraction of safe wells within 300 meters from the household; $S^{d,J}_{-h,v,t-1}$ is the fraction of neighbors in Group J at a distance d in village v from household h that switched water sources in $t-1$; $X^{G}_{h,v,t}$ refers to household-level covariates like income, education and assets.

In the first case $S^{G}_{h,v,t} = S^{A}_{h,v,05-08}$, the switching decisions during 2005-08 of those households in Group-A that did not switch sources previously. $S^{d,J}_{-h,v,t-1} = S^{d,A}_{-h,v,03-05}$, the switching decisions during 2003-05 of Group-A neighbors at distance d in village v. In the second case $S^{G}_{h,v,t} = S^{B}_{h,v,Jan-Nov08}$, the switching decisions during Jan-Nov 2008 of households in Group-B , and $S^{d,J}_{-h,v,t-1} = S^{d,A}_{-h,v,03-Jan08}$, the switching decisions during 2003-08 of Group-A neighbors at distance d in village v.

Examining the effects of neighbors' actions from a previous period breaks down the simultaneity of actions between households and their neighbors. However households may behave like their neighbors because they are similar in time-invariant unobservable ways. This motivates the search for an instrument that would predict the switching decision of neighbors but not directly affect the household's decision to switch. The instrument should be correlated with the neighbors' switching decisions;

however, it should also be one that does not directly predict the decisions of the household in question, but affects its behavior only by affecting the behavior of its neighbors (exclusion restriction). Chapters 2 & 3 of the dissertation demonstrates that the most important predictor of switching is arsenic content of the tubewell being used. Arsenic levels are unlikely to be chosen by households, due to the geological processes that determine arsenic in a tubewell.[10]Therefore, the fraction of neighbors using unsafe tubewells would be an appropriate predictor for the switching decisions of those neighbors.

However, the arsenic-content of proximate tubewells is likely to not satisfy the exclusion restriction. This is because the fraction of proximate tubewells that are unsafe affects the set of alternative sources that are available to the household in question, thereby directly affecting the household's decision to switch (and violating the exclusion restriction). At the same time, households are more likely to observe the actions of their proximate neighbors rather than those of the far neighbors. Thus an instrument that can predict the switching decisions of proximate neighbors without directly affecting the switching decisions of the household is needed. Based on self-reported walking time, households walk around 300 meters to fetch water from their water-source. I therefore

[10] As shown in previous work by Madajewicz et al. (2007) and in chapter 3, arsenic levels are not correlated with household characteristics, due to the geological processes that determine arsenic in a tubewell. Van Geen et al. (2003) find great spatial heterogeneity in arsenic levels between 8-30 meters, with no obvious pattern, making it difficult to predict the amount of arsenic in a tubewell. In our study, 90% of tubewells are less than 30 meters deep.

use the fraction of unsafe tubewells beyond 500 meters as an instrument for proximate neighbors' actions.

I proceed by estimating equation (1) to examine the effects of neighbors within 100 meters, with 200 meters, with 300 meters, within 400 meters, within 500 meters ,beyond 500 meters and the effects of all neighbors using ordinary least squares (OLS). I then use the fraction of unsafe wells beyond 500 meters from a household as an instrument in a two-stage least squares (2SLS) approach. Because these tube-wells are far enough, they are unlikely to affect the set of alternatives available to the household and thereby not violate the exclusion restrictions of the instrument[11]. I estimate the following equation as the first stage in the 2SLS approach:

$$S^{d,\hat{J}}_{-h,v,t-1} = \partial_0 + \partial_1 U^{>500,J}_{-h,v,t-1} + \partial_2 U^{G}_{h,v,t} + \partial_3 C^{G}_{h,v,t} + \partial_4 Safe^{<300}_{h,v,t} + \partial_5 X^{G}_{h,v,t} + \sigma^{d,J}_{-h,v,t-1} \qquad (2)$$

For Group-A households $S^{d,J}_{-h,v,t-1} = S^{d,A}_{-h,v,03-05}$ is the switching decisions during 2003-05 of Group-A neighbors at distance d in village v, and $U^{>500,J}_{-h,v,t-1} = U^{>500,A}_{-h,v,03-05}$ is the fraction of Group-A wells greater than 500 meters away from household h (in group-A) in village v that were tested unsafe. For Group-B households $S^{d,J}_{-h,v,t-1} = S^{d,A}_{-h,v,03-Jan08}$ is the switching decisions during 2003-08 of Group-A neighbors at distance d in village v. Here $U^{>500,J}_{-h,v,t-1} = U^{>500,A}_{-h,v,03-Jan08}$ refers to the fraction of Group-A wells greater than 500

[11] Our set-up allows us to have only one instrument, therefore preventing us from using a Sargen test or a Hausmann test to check whether the instrument satisfies the exclusion restrictions.

meters away from household h (in Group-B) in village v that were tested unsafe. I use these predicted values of neighbors' switching actions from (2) for both cases to estimate equation (1).

4.4 Results

4.4.1 Using arsenic>500 meters as instrument

I first consider Group A to examine whether the switching decisions of Group-A neighbors during 2003-05 affect the switching decisions during 2005-08 of those Group-A households that did not switch during 2003-05. Table 13 displays results for this case. Panel A reports OLS results from estimating equation (1). There is no effect of neighbors' decisions in 2003-05 on households' switching decisions in 2005-08. In panel B, I instrument for neighbors' decisions using the fraction of Group-A wells more than 500 meters away from the household that were tested unsafe, and do not find an effect that is significantly different than zero. I also find that the excluded instrument is weak (except in column 7), as indicated by the partial F-statistic of the excluded instrument in Panel B, indicating that far arsenic is not a good predictor of the near-neighbors' actions.

I next consider Group B to examine whether Group-B households' decisions to switch during Jan-Nov 2008 are affected by the actions of Group-A neighbors taken any time from 2003 to January 2008. Table 14 displays results, adjusted for clustering at the village level. I find a positive a significant effect of the switching actions of neighbors within 200 meters, 300 meters, 400 meters and 500 meters using OLS (panel A). Using

2SLS (panel B), the actions of neighbors do not have any effect on a household's decision to switch. The partial F-statistic for the excluded instrument suggests that it is weak; again indicating that far arsenic is not a good predictor of near neighbors' actions.

4.4.1 Using neighbors' own arsenic as instrument

I also re-estimate the 2SLS models by instrumenting neighbors' switching decisions using the fraction of their wells that are unsafe, rather than using the fraction of wells beyond 500 meters that are unsafe. Results are found in Panel C on Table 13 and Table 14. For Group-A households, I find that the effect of neighbors' actions on households' decisions to switch becomes negative, but it continues to be statistically insignificant from zero. Neighbors' own arsenic predicts their switching decisions, as indicated by the F-statistic on the excluded instrument in the first stage.

For Group-B households, there continues to be no effect of neighbors' switching decisions. Neighbors' own arsenic predicts their switching decisions better than arsenic beyond 500 meters (comparing the partial F-statistics between the two specifications); however, the partial F-statistic for the first stage indicates that the instrument is still weak, except when examining the effect of all neighbors. [12,13]

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[12] I have also tried to estimate the following cases using a instrumental variables strategy as described in methods section: (1) Effect of Group-A neighbors' decisions on Group-A households' decisions, both during 2003-05 ;(2) Effect of Group-A neighbors' decisions during 2003-08 on the decisions of Group-A households during 2005-08; (3) Effect of all neighbors (A & B) on Group-B households' decisions; (4) Effect of Group-B neighbors' decisions on Group-B households, both during 2008. (1) & (4) are cases of simultaneous actions, while (2) and (3) are a mix of sequential and simultaneous actions. The nature of results is substantively similar in all cases, and similar to the two cases reported in this chapter.

4.5 Discussion

The results in this chapter are mixed. I find no evidence of Group-A neighbors' actions on Group-A household's decision to switch, and some evidence of Group-A neighbors' actions on Group-B households' decision to switch sources. The effects in the latter case are likely endogenous and require an instrumental-variables approach in order to get an unbiased estimate of the effect. Far arsenic is not a strong predictor of near-neighbors' switching decision, likely due to the geological variability of arsenic in the shallow water-table, thus making far arsenic a weak instrumental-variable for near neighbor switching. Neighbors' own well-arsenic predicts their switching decisions, but is likely to fail the exclusion restrictions by also directly affecting the household's decision to switch. Therefore, arsenic may not be an appropriate instrument to identify the effect of neighbors' actions on a household's behavior, motivating the search for another instrument.

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[13] The two-step procedure by Bajari et al. (2006) may provide an alternative method to estimate neighbors' effects, rather than an instrumental variables approach. A few factors limit the application of this estimation method in this case. Firstly, Bajari et al. (2006) model their process as a static game of incomplete information, that does not involve any observation of others' action or any opportunities for learning by observing. Secondly, the data on household characteristics was recorded in 2008, after switching decisions has been taken by households in Group-A, and this hampers the ability of these characteristics to predict household switching decisions. However, I try to employ this method, purely as an econometric exercise. The first stage from both cases has F statistics of 1.22 & 1.26 respectively and R-squared of 0.00 & 0.00 respectively, and performs poorly in predicting switching decisions of neighbors. For brevity, I do not report these results.

Additionally, networks may not necessarily be defined by proximity. Water-source decisions, as well as the task of fetching the water, are the responsibilities of women. Perhaps an understanding of the nature of female social-networks by asking women detailed questions on the individuals they are interacting with (Ostor & Thornton 2008, Conley & Udry 2010) may reveal the composition of networks as well as the lag between neighbors' and individuals' actions (Manski 1993) which would help identify the effects of neighbors' actions on individual households.

Table 11: : Summary statistics: Group-A & Group-B

	All households		Difference (B-A)	
	Mean	Std Dev	Mean	Std Dev
Income				
Household food consumption: monthly *	4996.62	(3625.1)	-410.58	(172.81)**
Household Expenditure : monthly*	6161.75	(4350.21)	-296.54	(192.3)
Household expenditure on medicines: monthly*	517.34	(997.66)	49.62	(60.55)
Household Income: monthly*	8033.62	(8115.4)	-487.34	(393.67)
Brick Walls	0.12	(0.33)	-0.02	(0.02)
Sanitary latrine	0.79	(0.41)	-0.05	(0.03)
Demographics				
Respondent age	39.46	(13.24)	-2.99	(0.63)***
Respondent female	0.99	(0.17)	-0.00	(0.01)
Respondent primary water-source decision maker	0.98	(0.15)	0.02	(0.01)***
Respondent literate	0.43	(0.49)	-0.06	(0.03)**
Family Size	5.59	(2.49)	-0.34	(0.15)**
# children	2.11	(1.57)	0.16	(0.08)**
Fraction households with arsenic symptoms in at least one member	0.07	(0.25)	-0.04	(0.01)***
Fraction household members with primary education	0.59	(0.27)	-0.05	(0.02)***
Fraction household members with secondary education	0.28	(0.27)	-0.07	(0.01)***
# children in school per household	1.13	(1.12)	0.01	(0.05)
Social interactions				
Arsenic-induced illnesses: neighbors	0.03	(0.17)	-0.02	(0.01)**
Arsenic-induced illnesses: relatives same village	0.02	(0.13)	-0.01	(0.01)*
Arsenic-induced illnesses: relatives other village	0.01	(0.09)	-0.01	(0.00)**
Arsenic-induced illnesses: friends same village	0	(0.07)	-0.00	(0.00)
Arsenic-induced illnesses: friends outside village	0.00	(0.06)	0.00	(0.00)
Arsenic-induced illnesses: village leader	0	(0.05)	0.00	(0.00)
Discussed arsenic risks: household members	0.46	(0.49)	-0.09	(0.02)***
Discussed arsenic risks: neighbors	0.27	(0.45)	-0.10	(0.02)***
Discussed arsenic-risks: relatives same village	0.14	(0.35)	-0.04	(0.02)*
Discussed arsenic risks: relatives outside village	0.04	(0.2)	-0.04	(0.01)***
Discussed arsenic risks: friends same village	0.06	(0.24)	-0.02	(0.01)
Discussed arsenic risks: friends outside village	0.02	(0.15)	-0.02	(0.01)***
Discussed arsenic risks: village leader	0.01	(0.12)	-0.01	(0.00)*
Named households with tested wells (#)	1.54	(1.33)	-0.31	(0.10)***
Distance				
Distance to closest safe well (meters)	41.72	(120.02)	44.84	(33.09)

1.Source: Authors' 2008 survey

2.All income and expenditures derived from simple one-shot questions.

3. All monetary units are in Takas; Purchasing power parity of 23 Takas per US$.

Table 12: Summary statistics: mapping households to neighbors

	Group A (Case 1)	Group B (Case 2)
Fraction of households that switched	0.19 (0.40)	0.25 (0.43)
Fraction of households tested unsafe	0.61 (0.49)	0.62 (0.49)
Closest safe well to household	32.43 (51.74)	78.03 (224.57)
Fraction of safe wells <300 m of household	0.05 (0.17)	0.09 (0.20)
Fraction of neighbors < 100 m away that switched	0.18 (0.21)	0.36 (0.25)
Fraction of neighbors < 200 m away that switched	0.18 (0.18)	0.34 (0.17)
Fraction of neighbors < 300 m away that switched	0.18 (0.17)	0.33 (0.15)
Fraction of neighbors < 400 m away that switched	0.18 (0.16)	0.33 (0.14)
Fraction of neighbors < 500 m away that switched	0.18 (0.16)	0.34 (0.12)
Fraction of neighbors >500 m away that switched	0.17 (0.14)	0.33 (0.19)
Fraction of neighbors that switched	0.18 (0.10)	35 (0.10)
Fraction of neighbors < 100 m away tested unsafe	0.66 (0.29)	0.67 (0.28)
Fraction of neighbors < 200 m away tested unsafe	0.65 (0.26)	0.67 (0.23)
Fraction of neighbors < 300 m away tested unsafe	0.65 (0.24)	0.67 (0.21)
Fraction of neighbors < 400 m away tested unsafe	0.65 (0.24)	0.67 (0.20)
Fraction of neighbors < 500 m away tested unsafe	0.66 (0.24)	0.68 (0.19)
Fraction of neighbors >500 m away tested unsafe	0.67 (0.24)	0.72 (0.24)
Fraction of neighbors test unsafe	0.66 (0.19)	0.68 (0.18)

1. Figures in parentheses report standard errors

Table 13: Group-A households

	< 100 m	<200 m	<300 m	<400m	<500 m	> 500 m	All
Part A: Ordinary Least Squares							
Unsafe	0.12 (0.03)***	0.11 (0.03)***	0.11 (0.03)***	0.11 (0.03)***	0.11 (0.03)***	0.10 (0.03)***	0.11 (0.02)***
Closest Safe Well	0.03 (0.03)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)	0.04 (0.03)	0.04 (0.02)
Fraction safe wells< 300m	-0.03 (0.06)	-0.00 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.9 (0.06)
Fraction neis switched	**0.00 (0.06)**	**-0.00 (0.06)**	**-0.04 (0.07)**	**-0.06 (0.07)**	**-0.06 (0.07)**	**-0.05 (0.08)**	**-0.08 (0.11)**
Constant	0.11 (0.02)***	0.11 (0.02)***	0.12 (0.02)***	0.12 (0.02)***	0.12 (0.02)***	0.12 (0.02)***	0.13 (0.03)***
N	1192	1226	1233	1236	1236	1237	1276
R-squared	0.03	0.03	0.02	0.03	0.03	0.03	0.02
Part B: Instrumental Variables using fraction of unsafe wells beyond 500 m as instrument							
Unsafe	0.09 (0.04)**	0.09 (0.04)**	0.09 (0.04)**	0.09 (0.03)***	0.09 (0.04)**	0.13 (0.04)***	0.09 (0.03)**
Closest Safe Well	0.06 (0.04)	0.05 (0.04)	0.05 (0.04)	0.05 (0.04)	0.06 (0.04)	0.01 (0.05)	0.06 (0.04)
Fraction safe wells< 300 m	0.02 (0.08)	0.03 (0.07)	0.06 (0.09)	0.06 (0.09)	0.08 (0.09)	-0.04 (0.09)	0.07 (0.10)
Fraction neis switched	**0.71 (0.65)**	**0.68 (0.71)**	**0.98 (1.11)**	**0.97 (1.09)**	**0.97 (1.08)**	**-1.17 (1.59)**	**0.95 (1.23)**
Constant	-0.02 (0.12)	-0.01 (0.13)	-0.07 (0.20)	-0.07 (0.19)	-0.07 (0.19)	0.31 (0.28)	-0.06 (0.23)
N	1094	1126	1133	1136	1136	1176	1176
First Stg Partial-F	F(1,1089)=9.6	F(1,1121)=10.70	F(1,1128)=5.5	F(1,1131)=6.1	F(1,1131)=6.3	F(1,1171)=3.5	F(1,1171)=11.9
Part C: Instrumental Variables using neighbors' own arsenic as instrument							
Unsafe	0.12 (0.03)***	0.12 (0.02)***	0.12 (0.03)***	0.11 (0.03)***	0.12 (0.03)***	0.13 (0.04)***	0.12 (0.03)***
Closest Safe Well	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.01 (0.05)	0.03 (0.03)
Fraction safe wells< 300 m	-0.03 (0.06)	-0.02 (0.06)	-0.01 (0.06)	-0.01 (0.06)	-0.01 (0.06)	-0.04 (0.09)	-0.03 (0.07)
Fraction neis switched	**-0.11 (0.20)**	**-0.22 (0.25)**	**-0.43 (0.29)**	**-0.41 (0.29)**	**-0.40 (0.31)**	**-1.17 (1.59)**	**-0.65 (0.41)**
Constant	0.13 (0.04)***	0.15 (0.05)***	0.19 (0.05)	0.18 (0.05)***	0.18 (0.06)***	0.31 (0.28)	0.23 (0.070***
N	1187	1219	1129	1233	1233	1176	1276
First Stg Partial-F	F(1,1182)=97	F(1,1214)=89	F(1,1224)=80.2	F(1,1228)=79.2	F(1,1228)=75.6	F(1,1171)=3.5	F(1,1171)=105.9

1. Values in parentheses report standard errors. Figures with ***, ** & * significant at 1%, 5% & 10% resp.

Table 14: Group-B households

	< 100 m	<200 m	<300 m	<400m	<500 m	> 500 m	All
			Part A: Ordinary Least Squares				
Unsafe	0.27 (0.04)***	0.27 (0.04)***	0.28 (0.05)***	0.28 (0.04)***	0.28 (0.04)***	0.20 (0.05)***	0.27 (0.04)
Closest Safe Well	0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Fraction safe wells <300 m	-0.18 (0.07)***	-0.16 (0.06)**	-0.15 (0.06)**	-0.13 (0.05)**	-0.13 (0.05)**	-0.31 (0.10)***	-0.17 (0.06)
Fraction neis switched	**0.17 (0.12)**	**0.29 (0.16)***	**0.37 (0.16)****	**0.40 (0.18)****	**0.51 (0.21)****	**-0.21 (0.12)**	**0.42 (0.27)**
Constant	0.05 (0.05)	0.00 (0.06)	-0.02 (0.06)	-0.03 (0.07)	-0.07 (0.07)	0.24 (0.07)***	-0.03 (0.10)
N	479	498	499	499	502	266	502
R-squared	0.12	0.12	0.12	0.12	0.13	0.09	0.12
			Part B: Instrumental Variables using fraction of unsafe wells beyond 500 m as instrument				
Unsafe	0.21 (0.05)***	0.23 (0.06)***	0.30 (0.14)**	0.31 (0.15)**	0.39 (0.28)	0.20 (0.05)***	0.15 (0.10)
Closest Safe Well	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.03)	0.00 (0.01)	0.00 (0.01)
Fraction safe wells <300 m	-0.23 (0.11)**	-0.16 (0.13)	-0.03 (0.31)	0.08 (0.46)	0.32 (0.93)	-0.29 (0.10)***	-0.45 (0.32)
Fraction neis switched	**0.34 (0.41)**	**0.61 (0.59)**	**1.16 (1.39)**	**1.37 (1.68)**	**2.61 (4.03)**	**-0.29 (0.27)**	**-1.05 (1.45)**
Constant	0.03 (0.18)	-0.08 (0.26)	-0.29 (0.57)	-0.38 (0.69)	-0.89 (1.65)	0.27 (0.09)***	0.59 (0.59)
N	249	261	262	262	265	265	265
First Stg Partial-F	F(1,14)=1.9	F(1,14)=1.3	F(1,14)=0.4	F(1,14)=0.4	F(1,15)=0.3	F(1,15)=2.4	F(1,15)=6.58
			Part C: Instrumental Variables using neighbors' own arsenic as instrument				
Unsafe	0.26 (0.05)***	0.28 (0.04)	0.28 (0.04)	0.28 (0.04)***	0.28 (0.04)***	0.20 (0.05)***	0.27 (0.05)***
Closest Safe Well	0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Fraction safe wells <300 m	-0.15 (0.10)	-0.16 (0.08)**	-0.16 (0.10)	-0.12 (0.11)	-0.15 (0.13)	-0.29 (0.10)***	-0.19 (0.08)**
Fraction neis switched	**0.38 (0.40)**	**0.24 (0.33)**	**0.29 (0.53)**	**0.48 (0.54)**	**0.33 (0.74)**	**-0.29 (0.27)**	**0.06 (0.49)**
Constant	-0.02 (0.15)	0.02 (0.12)	0.01 (0.19)	-0.06 (0.19)	-0.00 (0.27)	0.27 (0.09)***	0.10 (0.18)
N	478	498	499	499	502	265	502
First Stg Partial-F	F(1,38)=2.4	F(1,38)=2.6	F(1,38)=1.4	F(1,38)=1.4	F(1,38)=1.1	F(1,15)=2.4	F(1,38)=13.1

1. Values in parentheses report standard errors. Figures with ***, ** & * significant at 1%, 5% & 10% resp.. 2. results adjusted for clustering at village level

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Biography

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