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Household Drinking Water Treatment in Rural China: Microbiological Effectiveness and Socioeconomic Predictors

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Household Drinking Water Treatment in Rural China:
Microbiological Effectiveness and Socioeconomic Predictors

By

Alasdair Gordon Cohen

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Committee in charge:

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Abstract

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Doctor of Philosophy in Environmental Science, Policy, and Management

University of California, Berkeley

Professor Jeffery M. Romm, Co-Chair
Professor Isha Ray, Co-Chair

Across the world, well over one billion people lack access to safe drinking water. There are a variety of low cost household drinking water treatment technologies available, but hitherto none have achieved widespread adoption. Globally, boiling is the most common treatment method.

Over the last few decades, China has achieved historically unprecedented reductions in rural poverty and concomitant expansions of piped drinking water access. However, hundreds of millions of rural Chinese still lack reliable access to safe drinking water. Most households in rural China boil their drinking water, often using biomass or coal for fuel. Though boiling is microbiologically effective, once it cools boiled water is susceptible to recontamination, and the combustion of solid fuels for boiling creates hazardous air pollution.

This research sought to evaluate the microbiological effectiveness of the household water treatment methods used in rural China, and to investigate the socioeconomic predictors associated with water treatment methods and preferences.

To conduct this research, I collaborated with the National Center for Rural Water Supply Technical Guidance, an agency of the Chinese Center for Disease Control and Prevention, and their counterparts in Guangxi Province. In 2013 we collected survey and water quality data from 450 households across 15 villages. Household drinking water samples were analyzed for indicators of fecal contamination and physicochemical analyses were conducted for village drinking water sources. Data collection was repeated in a subset of villages over the 2013-2014 winter to address seasonality, and remote temperature sensors affixed to kettles and pots were used to corroborate household survey responses about boiling frequencies and durations.

As far as I am aware, this was the first research study in China focused on household water treatment, and the first to quantify the advantages of boiling with electric kettles.

For my parents,

Mairi MacRae and Richard Cohen

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Oakland

Chapter I

Introduction

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1. Introduction

> "The evolution of ecosystems with living components that we recognize as the biosphere buffers the raw physical processes that create and destroy matter. This sophisticated and delicate living skin on the surface of the Earth regulates the movement and quality of water in ways that perpetuate its own well-being and that of humankind."
>
> (Hunt, 2004: 6)

> "[Water] Scarcity is manufactured through political processes and institutions that disadvantage the poor…
>
> (UNDP, 2006: 3)

> "The identification of a problem is intimately linked to the availability of a solution… the practice of 'rendering technical' confirms expertise and constitutes the boundary between those who are positioned as trustees, with the capacity to diagnose deficiencies in others, and those who are subject to expert direction."
>
> (Li, 2007: 7)

This chapter provides a broad introduction to the sectors and research areas within which I conducted my doctoral research as well as a window into my initial approach and framing for this research project and some of the literatures which motivated my initial inquires.

This research was initially motivated by a desire to determine if one of the currently available household water treatment (HWT) technologies might usefully be promoted in rural China to expand access to safe drinking water. Consequently, much of my initial focus was on HWT adoption specifically.

As it turned out, the results suggested that rather than attempting to introduce a new HWT technology (an incredibly challenging proposition), the "best" strategy might well be to build upon the predominant existing HWT method: boiling water.

2. Background & context

Over the last few decades, great progress has been made in the water, sanitation, and hygiene (WASH) sectors of low and medium income countries. Yet, more than 1.8 billion people still lack access to safe drinking water (WHO/UNICEF, 2014, Bain et al., 2014a), and ~500,000, mostly children, die from diarrhea each year as a result (Prüss-Ustün et al., 2014).

In particular, the lack of access to safe drinking water is a predominantly rural problem (Bain et al., 2014b), and despite extensive efforts, sustained adoption and consistent use of HWT remain elusive goals in low and middle-income countries (Figueroa and Kincaid, 2010, Waddington et al., 2009, Arnold and Colford, 2007, Rosa et al., 2014).

2.1 WASH inequalities and human and environmental health

Human and environmental health are intimately linked by water. The ways we use, manage, contaminate and safeguard water directly impact the ecosystems upon which our biosphere and hydrosphere rely. Overuse of surface and groundwater resources and their contamination with wastewater, urban runoff, mine drainage, pesticides, herbicides, nitrates, phosphates and industrial effluents severely strains hydrologic cycles and their natural water filtering capacity. For those with no viable choice but to consume contaminated surface and groundwater, impoverished environmental health negatively impacts human health.

Generally, the lack of access to safe water is more prevalent in rural areas than in urban ones and, in absolute terms, the problem is more severe in Asia than in any other region. In rural areas surface water, water from shallow wells or improperly stored rainwater, are often contaminated with pathogens.

The multiple links between water contamination, sanitation, hygiene and health are well established (UN, 2005), as is the connection with poverty, in part because a “lack of safe water perpetuates a cycle whereby poor populations become further disadvantaged, and poverty becomes entrenched” (WHO, 2007: 7). Safe water supply, treatment, proper storage and appropriate sanitation and hygiene can improve health and help reduce poverty; however, achieving equitable access to these services remains a challenge.

In much of the world, the roots of this global WASH problem are more political than hydrological and thus those with the least power and voice tend to be most severely affected. Indeed, “the crisis in water and sanitation is, above all, a crisis of the poor in general and of women in particular” (UNDP, 2006: 27).

2.2 The historic top-down and technical framing of safe water provision

In order to understand the larger historical context within which contemporary WASH interventions are designed and implemented, it is appropriate to reflect, if only briefly here, on the legacies of development and the political drivers involved.

"Development", as is used in the WASH sector, is a complex catch-all term for an array of physical and social infrastructure interventions in low and middle-income nations (Hall, 1992, Kothari, 2005) which are often portrayed in practitioner and academic literatures as either humanitarian efforts to be taken at face value or as a means to expand the frontiers of capitalist exploitation and resource extraction. For much of the 20th century, when rural water supply was provided it was done in a top-down, command-and-control fashion with (arguably) insufficient input from would-be users.

This paradigm has changed in the last few decades with a shift towards participatory development, with both its new-left and new-right variants (Mohan and Stokke, 2000, Hart, 2001, Cooke and Kothari, 2001). However, after decades of work in this area, achieving sustained access to safe drinking water is a goal which remains elusive. In rural areas of many low-income countries it is not yet economically or politically feasible to provide centralized treatment and distribution. Consequently, point-of-use HWT options are often promoted.

In this context, HWT can be viewed either as a stop-gap measure until centralized treatment can be provided (a more believable framing in countries like China as compared to countries with poor governance and limited resources), or as in fact a long-term solution for rural households which lack access to safe drinking water – one which puts the burden of responsibility of safe water on rural residents themselves.

With regard to framing generally, it is the contextualization of development problems like safe water provision in largely technical terms which often in turn limits the array of would-be solutions for addressing them (Ferguson, 1994, Scott, 1998, Mitchell, 2002, Li, 2007). As a consequence, many of the offered interventions seek to ameliorate the symptoms (e.g., unsafe drinking water) rather than the underlying causes (e.g., industrial contamination) which are, often, political in nature.

With this understanding in mind, looking back over the last few decades, the legacy of framing WASH problems in largely technical terms can be better understood and helps to partially explain the inordinate focus on new HWT technologies, efficacy trials, and top-down information campaigns for HWT promotion. Only recently has the WASH and HWT literature started to pull-back from these technology-centered framings to examine socio-cultural and behavioral factors.

3. Household water treatment and the challenge of achieving adoption

Research on HWT technology has yielded impressive results, and epidemiological trials have helped clarify which technologies work in the field as well as the lab (Fewtrell et al., 2005, Waddington et al., 2009). Ceramic filters, bio-sand filters, chlorine (with/without flocculation), solar disinfection, and ultraviolet light, can all be efficacious methods for HDWT if used correctly (Lantagne et al., 2007), though removing naturally occurring arsenic and fluoride requires specialized media. Yet HWT technology alone will not help us address these larger problems.

3.1 An array of effective HWT technologies with limited adoption

What is the "best" HWT technology? Part of the problem answering this question depends on how "best" is defined. Is it based on log-rates of pathogen removal/inactivation? Or the rate of sustained adoption over 10 or 20 years? Or other factors?

A number of well-designed studies have examined the efficacy of ceramic filters in real-world conditions (e.g., Clasen et al., 2005, Brown et al., 2008, du Preez et al., 2008). This and other evidence suggests that ceramic filters may have the most promise for achieving sustained use/adoption among (Lantagne et al., 2007, Sobsey et al., 2008), possibly because they are easy to comprehend, easy to use, require little maintenance, and do not change the taste of the water. Biosand filters are another promising option with respect to long-term adoption potential, though rates of pathogen removal should be investigated further (especially when the sand media is not regularly changed/cleaned); the installation costs are also a considerable barrier for many poor rural households (Sobsey et al., 2008, Hunter, 2009, Stauber et al., 2009, Elliott et al., 2008, Tobias and Berg, 2011).

Unfortunately, almost regardless of the specific HWT technology, achieving sustained adoption of HWT in poor rural areas, at any scale, is incredibly challenging and most HWT interventions yield relatively low adoption rates, which fall further after the interventions conclude. There are many reasons why this is the case.

Studies on arsenic and fluoride remediation note that, in addition to the role of social factors, if contaminated water looks, smells and tastes fine, then households will be unlikely to switch sources or treat it (Ahmad et al., 2007, Mosler et al., 2010). Yet even when water does not look or taste "clean" many households may report being satisfied with their water quality. Arnold et al. (2009: 5) found that "85% of study households [in Guatemala] were satisfied with their drinking-water quality, but only 65% of respondents believed their drinking water was clean".

Taste is another factor. Research in Kenya promoting chlorine (sodium hypochlorite) found that while some households felt chlorine made their water taste bad, others found it "sweetening" (Kremer et al., 2008-draft).

In addition to these issues, regardless of the specific HWT technology, when individuals in households using HWT become ill, they may lose faith in the benefits of HWT and stop treating their water unaware that the illness may well have been food-borne, for example (Figueroa and Kincaid, 2010).

Another example is SODIS: disinfection achieved by placing water in bottles under the sun. Though SODIS is an excellent HWT method with regard to cost, east of use and pathogen inactivation/removal – but a very unappealing method for would-be users, which is why achieving sustained adoption of SODIS is especially challenging (Tamas and Mosler, 2011, Mäusezahl et al., 2009, Arnold et al., 2009).

3.2 Looking beyond the technology to achieve sustained HWT adoption

Clearly, changing people's health-related attitudes and behaviors is a highly complicated and challenging endeavor (Cialdini, 2009, Hardeman et al., 2002). To better understand HWT adoption then it is arguably crucial to understand what types of people and households use which types of HWT. However, looking back over the last few decades of WASH research, most HWT studies were more concerned with identifying which HWT technology was most efficacious (e.g., Albert et al., 2010, Luoto et al., 2011), rather than which methods of introducing HWT were most effective.

In light of the overwhelming evidence of low HWT adoption across technologies, it is not surprising that "the scarcity of papers on behavior change with respect to point-of-use [HWT] water treatment technologies suggests that this field is underdeveloped" (Fiebelkorn et al., 2012: 623). For those technologies that are clearly efficacious but not yet being scaled up, the safe drinking water research and literature is now, finally, turning to the challenges of behavior change, and of technology uptake and adoption in low-resource communities.

Innovation Diffusion research suggests that "preventative interventions" like HWT are adopted slowly, if at all, when it is challenging for would-be users to perceive the benefits over the status quo (Rogers, 2003). While it is indeed the case that characteristics of any technology are relevant to its adoption, as the last few decades of HWT promotion efforts demonstrate, this is only part of the puzzle.

How a given technology is introduced or promoted is a crucial factor as well. For example, education and information campaigns, even highly targeted ones, do not appear to reliably spur long-term HWT or WASH-related adoption and, overall, the relative lack of research on the socio-behavioral aspects of HWT adoption is a factor as well (Figueroa and Kincaid, 2010, Kraemer and Mosler, 2010, Mosler and Kraemer, 2011, Freeman et al., 2012, Fiebelkorn et al., 2012).

Behavioral research (not specific to WASH) suggests that "tailored health communication" is more effective at motivating health-related behavior change than generic, one-size-fits-all, information (Smeets et al., 2007, Noar et al., 2011, Kreuter and Wray, 2003). This finding can be applied to HWT promotion. A few studies (e.g., Jalan and Somanathan, 2008, Davis et al., 2011, Luoto et al., 2009) have evaluated the impact of sharing water quality test results with households to help them understand that their water is contaminated, and that HWT can make it safe to drink. Thus far, however, even this approach does not appear to be especially effective (Lucas et al., 2011).

Indeed, the broader literature on rural development, participation and natural resources management shows clearly that custom-tailoring projects to the local context is crucial for success (IFAD, 2010). Projects implemented without accounting for contextual factors, culture and history are less effective than those that do, at best, and fail miserably at worst (Chambers, 2008, Roe, 1991). Local people are often best placed to understand the potential demand for a new technology and how community members might be motivated to use it. There is evidence for this in the literature on development and participation in natural resource management (e.g., Ostrom, 1990, Mohr and Smith, 1999, Mosse, 2003, Blanton et al., 2010), as well as community-based participatory research on health (e.g., Leung et al., 2004, Minkler and Wallerstein, 2008, Wallerstein and Duran, 2006). One of the few studies to examine this with regard to water provision concluded that there is "clear evidence that beneficiary participation does indeed lead to better project outcomes" (Manikutty, 1997: 116).

Technologies or methods that are relatively user-friendly, easy to comprehend, easy to demonstrate and have an advantage over the status quo are indeed more likely to be adopted (Rogers, 2003). Taking all of this into consideration, it should not be surprising that boiling remains the most commonly used HWT method ("technology") globally (Rosa and Clasen, 2010).

Yet HWT adoption is not based just on the technology or the way it is introduced, rather: "Water treatment behavior is clearly related to many other individual beliefs and values, family relationships, social norms and ecological factors." (Figueroa and Kincaid, 2010: 3). Indeed, as Figueroa and Kincaid discuss, in many communities diarrhea may be viewed as a normal part of children's development, or the body "cleaning" itself; similarly, cultural preferences can even motivate people to consume untreated water when treated water is available.

In order to better understand existing socio-cultural barriers to adoption it is therefore necessary to first understand the would-be HWT users and their current beliefs and behaviors around WASH. Such an understanding can then facilitate the design of a HWT intervention. Problematically, "few impact evaluations addressing sustainability [of HWT use] collect data on the reasons for the levels of compliance and acceptance" (Waddington et al., 2009: 3), so we lack a clear understanding of why HWT use is often so short-lived.

4. Safe water access in rural China: Achievements and challenges

> In China, "…safe drinking water is not only a public health problem but a more comprehensive problem related to basic public service equalization, sustainable economic development, social justice and social stability"
>
> (Li et al., 2015: 442).

Though China is responsible for a disproportionate share of the global WASH gains in recent decades (WHO/UNICEF, 2014), very little is known about drinking water quality or HWT in China. This is in part because available data is almost all in Chinese-language journals and government reports, and because of the politically "sensitive" nature of water quality data in China. Of those Chinese sources that do discuss rural drinking water quality, few provide specific water quality data, and almost none disaggregate HWT methods or examine causal linkages between socioeconomic factors and water-related beliefs and behaviors.

4.1 Looking across the data/language barrier to China's WASH achievements

From 1990-2012 an estimated 488 million Chinese gained access to "improved" water sources (WHO/UNICEF, 2014). China's gains in the WASH sector, and historically unprecedented reductions in poverty, were largely the result of billions of dollars of investment in rural drinking water infrastructure since the early 1980s, as well as concomitant investments in rural electrification, roads, schools, health clinics, sanitation infrastructure, and (especially) agriculture (Montalvo and Ravallion, 2010, IFAD, 2010).

Data from China Health and Nutrition Surveys suggests China's ~8.8 billion USD investment in rural drinking water infrastructure from 1981-2002 is significantly associated with positive health outcomes for rural residents (Zhang, 2012)[1]. Thanks to these investments as well as decades of public health campaigns promoting improved hygiene, coupled with the cultural preference for boiled water, available data suggests that rates of diarrhea in rural China are quite low as compared to most low and middle-income countries (Zhou and Zhang, 2012).

While exposure to pathogens has fallen over the last few decades, concern over industrial and agricultural contaminants in drinking water continues to grow (Smil, 1993, Ma, 1999, Zhang et

[1] Zhang's analysis considers water supply from a treatment plant as an "improvement of water quality", versus access from other sources. This variable construction is problematic in many cases because most rural treatment plants in China do not regularly chlorinate drinking water and many are poorly managed. Overall this proxy of water quality is still useful (much like the JMP definitions of "improved" and "unimproved" sources), but the results should be interpreted with some caution.

al., 2010), a problem recent research has linked to negative health outcomes (e.g., Ebenstein, 2012).

Beyond such aggregated statistics, the global WASH community knows little about WASH or HWT specifically in China. This is in part because what research and data does exist is almost all in Chinese, and in part because water quality data has been, and remains, a "sensitive" issue in China.

A clear example of the language-barrier (and relative lack of data) surfaced in response to Rosa and Clasen's (2010) estimate that ~1.1 billion people use HWT worldwide; a figure they acknowledged did not include China due to the lack of available data. Yang, Wright, and Gundry replied (2012a) that according to a Chinese-language paper (Zhang et al., 2009), more than 600 million Chinese also use HWT – bringing the global estimate closer to 1.8 billion. This estimate was based on a 2006-2007 CCDC-led national survey (Tao, 2009), which found that ~85% of Chinese households regularly boil their drinking water.

With regard to present rates of safe drinking water access, the few available national estimates vary, a problem partially due to different definitions (Yang et al., 2012b). The most accurate, though somewhat outdated, estimate available is also from the CCDC-led 2006-2007 national survey, suggesting ~317 million rural Chinese lack access to safe water (Tao, 2009, Zhang et al., 2009).

Even when consulting Chinese-language reports and journal papers related to rural drinking water, relatively little specific water quality data is provided, with most only reporting microbial contaminant concentrations as being "above" or "below" government standards. To illustrate this point, for their recent meta-analysis of drinking water quality and fecal contamination, Bain et. al. (2014a) identified nine suitable studies from China, ranging from 2007-2012 (see the "water quality database" in their Supplemental Material; database ID numbers of the studies are: 265, 272, 273, 381, 424, 540, 543, 552, 553, 554, and 554 [two studies are used twice because they provide information on two types of water sources]). Though all nine studies used TTC as an indicator of fecal contamination to assess water source quality, none provided arithmetic or geometric means, or microbial risk classification data (column's "AC" to "AL" in their "water quality database"). This is typical of most Chinese water quality studies hitherto.

4.2 The benefits and costs of boiling drinking water in rural China

In China's most remote areas (often the poorest of the poor and minority ethnic groups living at higher elevations) many villages do not yet have piped water in or near their homes due to the high costs associated with conventional water treatment and distribution infrastructure. Even in another 10 or 20 years, it is unlikely that it will be economically or politically feasible to connect all remote rural households to centralized drinking water treatment systems (due to low-population densities and challenging topography).

In such areas, many rural households lack access to safe drinking water, a situation which negatively impacts their health and livelihoods. In response to this lack of access to safe water, and due to strong cultural factors/legacies as well, the majority of Chinese households boil their water before drinking it. While efficacious with regard to killing and inactivating pathogens, this approach to drinking-water treatment is problematic (especially when high concentrations of arsenic or fluoride, or other chemical contaminants, are of concern, since boiling merely concentrates them further).

Most of China's rural population uses wood and crop residues for fuel, and many use coal as well. Combustion of these fuels is the primary source of household air pollution (HAP) in rural China, meaning ~600 million people may be exposed to daily indoor air pollution from cooking food, heating their homes and, in most households, boiling water (Zhang and Smith, 2007). HAP from biomass and coal combustion causes cardiovascular and pulmonary disease, biomass harvesting is time-consuming, fuel is often costly for poor households, water boiled in pots is easily re-contaminated, and black carbon emissions exacerbate climate change (Bonjour et al., 2013, Ramanathan and Carmichael, 2008, Wright et al., 2004). In rural China, boiling remains the primary method of HWT.

Biomass harvesting also causes local environmental degradation and, once combusted, contributes to greenhouse gas (GHG) emissions (Rehfuess et al., 2006). What is more, it costs time and/or money to collect the fuel and wait for water to boil. In the aggregate, the negative public health, environmental and economic externalities of water boiling in rural China are likely considerable.

While there is some data on predictors of HAP exposure in rural China (e.g., Baumgartner et al., 2011), unfortunately, at present we lack a clear understanding of which fuels are used in rural Chinese households for water boiling. This is in part because measuring or predicting fuel usage based on economic growth and/or income is far from straightforward (Ekouevi and Tuntivate, 2012). Indeed, even as household incomes rise many rural households still use a variety of fuels at different times and/or for different purposes – termed "fuel stacking" (Masera et al., 2000). This is also the case in rural China, where households which can afford higher quality fuels (such as liquid petroleum gas) often still opt to use biomass for certain cooking or heating applications (e.g., see: Peng et al., 2010).

5. Research Questions

With a view toward people's long-term health and well-being, efforts should be made to understand if drinking-water treatment technologies or methods other than boiling might be more appropriate for rural communities in China, or if boiling is still the best option for the time being, negative externalities included.

A first necessary step is to better understand the current situation. As such, the broad research questions for this research were as follows:

- What methods of household water treatment are currently used in rural China, and how effective are they with regard to inactivating microbial pathogens?
- What types of people/households use different methods of HWT? What are the socioeconomic, demographic, or other variables associated with preference for boiling or another HWT method?
- Looking to rural China's future, what type of HWT technology (if any) might be appropriate for expanding access to safe drinking water until universal access to safe, piped, drinking water is achieved?

Over the course of the following chapters I will attempt to answer these questions.

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Chapter II

Data Collection Methods

Chapter II: Table of Contents

1. Introduction

This chapter provides a chronological explanation of the data collection and related methods used for this research. This study was reviewed and approved by the Committee for Protection of Human Subjects at UC Berkeley's Institutional Review Board (protocol ID: 2012-05-4368) and by the Chinese Center for Disease Control and Prevention (CCDC) Institutional Review Board in Beijing. Written consent was obtained from all participating households/respondents.

2. Field sites and sample selection

2.1 Selection criteria for field sites & initial sampling strategy

The following considerations and selection criteria were used to identify the field-sites:

1) Collect data at a wide enough scale to be able to draw conclusions about the population in question with regard to water-related behaviors and beliefs
2) Focus, at least in part, on the rural poor living in remote areas where the costs to provide centralized/piped water infrastructure are very high (due to low population density and rough topography)
3) Collect some of the same data at two time points: once during the summer (2013) and again during the winter (Dec 2013/Jan 2014), in order to examine seasonality effects.

Based on this selection criteria, in early 2013 I began discussing potential field sites with Yang Zhenbo (Water, sanitation, & hygiene [WASH] chief, UNICEF-China). We decided to limit our focus to four provinces where UNICEF's pilot project on mini-utilities was already underway: Guangxi, Sichuan, Shaanxi and Gansu. Initially, I had planned to work alongside UNICEF in both Guangxi and Shaanxi (in order to compare a water-rich region [Guangxi] with a relatively arid region [Shaanxi]); this comparison would have also been interesting due to the higher rate of coal use in Shaanxi as compared to Guangxi. However, due to the challenges with regard to data collection, time, and cost considerations, as well as other factors, I decided to initially undertake the research in Guangxi only. In addition, late in the spring of 2013, it became clear that UNICEF would not be able to formally collaborate on the research project, though Yang Zhenbo would continue to be involved and provide advice as needed. As such, the primary partner for the research collaboration was the National Center for Rural Water Supply Technical Guidance (NCRWSTG) at the CCDC, under the direction and supervision of NCRWSTG Director, Tao Yong.

2.2 Scoping visits to Guangxi and Shaanxi Provinces

At the end of March and into early April, 2013, Director Tao and I travelled to both Guangxi and Shaanxi Provinces (at that point we were still planning on working in both provinces) in order to meet the Provincial CCDC directors and visit one prospective county in each Province. The purpose of the trip was for me to be formally introduced to the Provincial CCDC staff and to discuss the research and incorporate feedback from the provincial and county CCDC.

We first travelled to Nanning, capital of Guangxi province where we met with Zhong Gemei, Director of the Institute of Environmental Health and Endemic Disease Control at the Guangxi Zhuang Autonomous Region Center for Disease Control and Prevention, and her Nanning-based staff. We then travelled to County A[1] to meet with the county CCDC (left image in Figure 1) and discuss the work plans. I also visited their county laboratory and we discussed the methods they use for microbial water quality analysis. In addition, we spent one morning visiting a few nearby villages (right image in Figure 1) where I had the opportunity to talk with local residents to get a clearer understanding of common drinking water related beliefs and behaviors, as well as fuel use, etc. In addition, the county CCDC called their staff in various townships to get rough estimates of boiling water prevalence (to help me with our sample size calculations). Lastly, I provided them rough drafts of the additional survey questions we were developing (discussed below) in order to get their feedback (unfortunately, very little feedback was provided).

Figure 1: County A, Guangxi: County CDC Offices (left) and staff (right: County A deputy director, driver, Tao, Cohen, Zhong, County A staff)

The same process/steps were followed in Shaanxi Province, where we met directly at the Xian airport with staff from the Provincial CCDC and travelled to Fuping County. As in Guangxi we discussed the research plans with them and asked for their feedback. We spent the next day visiting nearby villages to collect the same basic data/observations as in Guangxi (see Figure 2). Ultimately, we decided to focus our research efforts only in Guangxi for this project, but should the national CCDC wish to upscale the research in the future they will likely begin in Shaanxi Province.

[1] As per the request of the NCRWSTG and CCDC, due to the sensitivity of water-quality related data in China, rather than using place names I use alphabetic and numeric codes for the counties and villages where we collected data.

Figure 2: Images from Fuping, Shaanxi: Government-provided tap water, vented stove, large water kettle (left to right)

2.3 Power calculations

For our cross-sectional study design, our primary outcome variable was the percentage of households regularly boiling their drinking water. The best estimate we had for the national prevalence in China was 85.23% (Tao, 2009, Yang et al., 2012). With regard to Guangxi Province specifically, very rough data from our scoping trip (described above) suggested the proportion there (at least for parts of County A) was closer to 65%. Our partners at the Guangxi Province CCDC reported that, based on existing provincial data, their best estimate was that 68% of rural households regularly boiled their water, with ~20% using bottled water and ~10% consuming untreated water.

As such, I used this boiling prevalence estimate of 68% for our sample size calculations. Given the array of other indicators we would be measuring via the household surveys, it was also preferable to err on the side of caution (rather than using the national average of 85%) and have a larger sample size so as to have more power for our eventual analysis of other indicators (other than boiling prevalence).

Another important consideration in calculating sample size was that we were sampling households at the village level (i.e., cluster-level), with the plan of sampling 30 households per village (though the level of primary analysis was at the household level). Because there is usually a higher level of similarity, of correlation, between households in the same village versus households in different villages, we needed to factor this intracluster correlation into our sample size calculations.

Based on rough estimates of boiling prevalence in different villages in County A County, I used an estimated intracluster correlation coefficient (ICC) of 0.01. This ICC value, usually referred to using the Greek *rho* (ρ), is calculated by comparing the variance (of boiling water in this case) within villages/clusters with the variance between villages/clusters. In our case we did not have sufficient pilot data with which to calculate *rho*, which is why I used the estimate of 0.01.

This value was then used to calculate the design effect (DEFF) which allowed us to correct our would-be sample size to factor in the impact of this within and between cluster variance. The DEFF was based on *rho* and the size of our clusters (30 households per cluster) as shown in Equation 1.

$$DEFF = 1 + (\overline{\mathrm{m}} - 1)\rho$$

Equation 1: Design effect (DEFF)

Where

$\overline{\mathrm{m}}$ = 30 (number of households in each village/cluster – which we held constant at 30)
ρ = 0.01 the Intracluster Correlation Coefficient (estimate)

We then used the DEFF of 1.29 to calculate our sample size using Equation 2.

$$n = \left[z^2\left(\frac{pq}{d^2}\right)\right]DEFF$$

Equation 2: Sample size calculation (total number of households)

Where

$z^2 = 1.96^2$ (95% confidence interval)
p = 0.68 (estimate of regular/daily water boiling prevalence)
q = 0.32 (1-p)
$d^2 = 0.05^2$ (precision required is 5%) [note: in other formulas "m" is used instead of "d"]
DEFF = 1.29

This calculation yielded a total sample size of: n = 431 (households)

As outlined above, the sample size was to be split among two counties, with 30 households sampled per village. Given these considerations, and that I used an estimate of *rho*, we opted to increase our sample size from 431 to 450 (with this increased sample size, we were now working with an effective *rho* of 0.012 and an effective *DEFF* of 1.348).

This allowed us to sample 210 households in the higher income county, County B, and 240 households in the lower income County A (given the research focus on rural poverty, we intentionally assigning the "extra" 15th village to the low-income county). Thus, we selected seven villages in County B and eight in County A, for a total of 15 villages (see Figure 3). Thus, our final sample size was 450 households.

For additional details, see Appendix III.

2.4 Multi-stage, stratified sampling approach & resulting villages selected

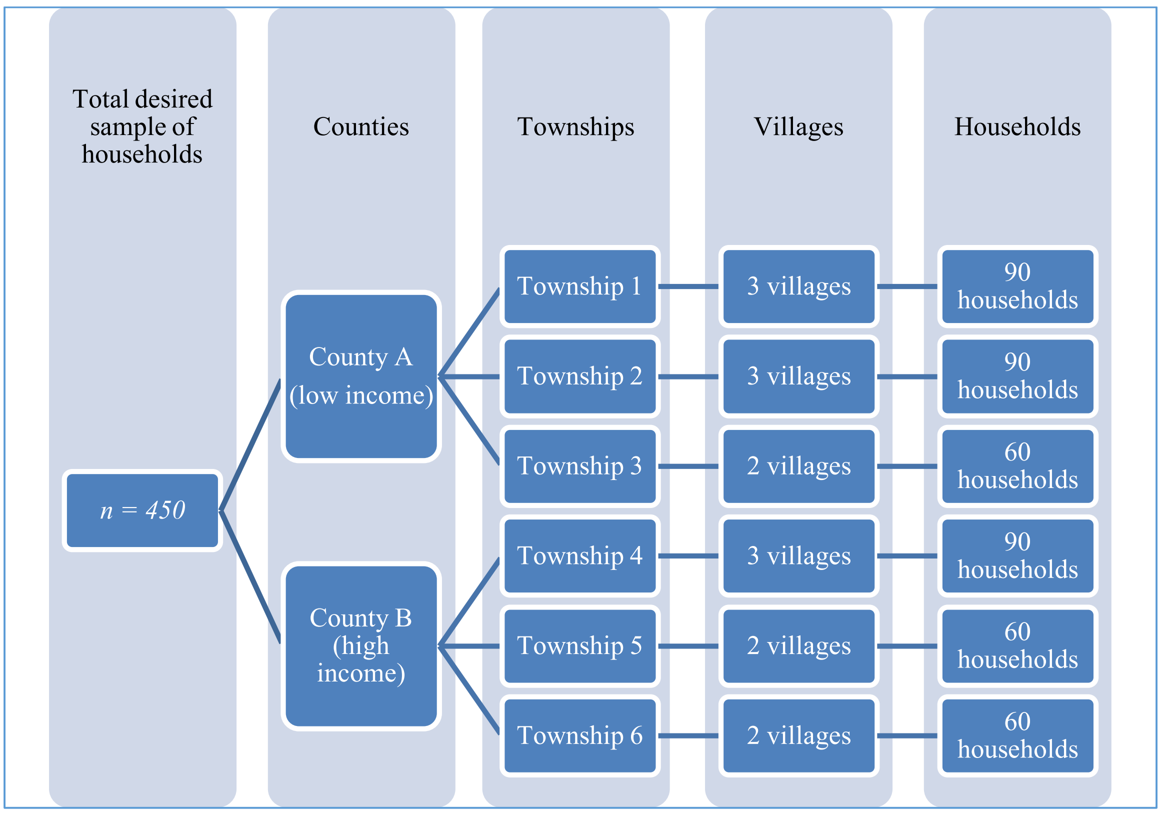


Figure 3: Overview of multi-stage sampling approach to select study households for Summer 2013 data collection

The household survey data as well as the household water quality data was collected using a cross-sectional study design since this provided a snapshot of the current conditions which could be generalized to the larger population from which the sample was taken.

To conduct a geographically stratified, random, representative survey, multi-stage cluster sampling was used to identify villages/clusters within which we then randomly sampled a constant of 30 households per cluster/village. As shown in Figure 3, two counties were selected, and within each three townships, and then eight and seven villages selected from those townships.

To arrive at the randomly sampled households we followed these steps:

1. First, the sampling universe was defined by creating a list of candidate counties[2] which were designated as either high, medium, or low with regard to income/economic development using household income data from previous, province-wide, rural household surveys (though rural income data is notoriously unreliable, on the aggregate this data provided a sufficient proxy of the level of economic development by county).
2. In consultation with Zhong Gemei and our CCDC counterparts in Guangxi, and using other aggregate data, we selected one high income county and one low income county. The two primary indicators used to help make this selection were: average rural income and the percentage of the county that is considered rural. Relevant information (used as partial selection criteria) for the two selected counties is provided in Table 1.

Table 1: Data used to help select the two survey counties

County	Population	Rural Population	% rural	Number of admin. villages	2012 mean rural income (RMB)	2012 mean rural income (~USD)*	% with centralized water treatment	% of households boiling water
A	680,726	626,010	92.0%	243	4,047	642	35.5%	60%
B	1,042,082	819,358	78.6%	190	6,180	981	96.4%	48%

Sources: Government census data, except boiling prevalence estimates which are from the Guangxi CCDC
*2012 average exchange rate: USD 1 = RMB 6.3

3. With the two counties selected, we then generated lists of all the townships in each of these two counties and their population data. These lists were used to randomly select three townships in each county using population-based proportional sampling (also known as sampling based on probability proportional to size).
4. We then generated lists of all the administrative villages in each of these six townships as well as their populations, and then used the same sampling strategy (population-based proportional sampling) to select two or three villages in each township for a total of 15 villages. The results are presented in Table 2 and Table 3 for each county, in addition the village codes used in this dissertation and related publications are provided.
5. Lastly, the protocol agreed to was that at the village level when the enumerator teams first visited the village they would meet with the village leader/official and use lists of all

[2] In China, the basic administrative hierarchy is: Province, County, Township, Administrative Village, Natural Village.

the households in the village to randomly select 30 households in each village (with additional households selected to address non-response). Specifically, this was done by cutting out numbered tabs, one for each household in the village, and then having the village leader/official randomly select 30 which were marked on the list of households. The village leader/official then proceeded to select additional households which were to be sampled when some of the original 30 were unable or unwilling to participate. In the event that more than 20% (six households) of the initial sample of 30 did not participate, the enumerator team supervisor would talk to the village leader/official to get the following data about those households that did not participate: their relative economic status (better or worse than the village average) and their relative household population (larger or smaller than the village average).

Table 2: List of randomly selected townships and villages in County A

Township	Village code	Population (2012)	Mean income	Replacement Villages		Final Sample	
				Population (2012)	Mean income	Population (2012)	Mean income
A.1	1	4,247	3,698	-	-	4,247	3,698
	2	1,407	3,256	5,898	3,768	5,898	3,768
	3	2,269	1,860	2,025	2,984	2,025	2,984
A.2	4	6,388	5,052	-	-	6,388	5,052
	5	5,863	5,179	-	-	5,863	5,179
	6	3,781	4,868	-	-	3,781	4,868
A.3	7	7,373	4,830	-	-	7,373	4,830
	8	8,890	7,864	5,640	5,021	5,640	5,021
Total/Mean:		**5,027**	**4,576**	**4,521**	**3,924**	**5,152**	**4,425**

Table 3: List of randomly selected townships and villages in County B

Township	Village code	Village Population (2011)	Mean income
B.1	9	6,402	7,715
	10	5,589	6,630
	11	3,341	8,526
B.2	12	3,635	6,570
	13	7,271	6,970
B.3	14	6,256	5,000
	15	3,035	7,510
Total/Mean:		**5,076**	**6,989**

Note: Modifications to the original sampling frame/plan
The CCDC staff in County A felt it would be too time consuming to survey three of the randomly selected villages (2, 3, and 8) due to their locations and the great difficulty involved in reaching them (remote, poor quality roads, etc.). After initial discussion to try and persuade them to continue with the original sampling frame, a compromise was reached: namely, that the CCDC staff in County A would select three replacement villages that were roughly similar to the original three, using population and income as the primary proxies for making this decision. The initial and replacement villages are described in Table 2 (though the population and mean income figures are not as close to the originally sampled villages as would have been desired). This compromise was not ideal from a sampling point of view, but was ultimately necessary if the research was to move forward.

This sampling method is similar to that used for The Multidimensional Poverty Assessment Tool (MPAT)[3], which was our primary tool for the rural household surveys. Originally, I had hoped to also use the MPAT Village Surveys, but the CCDC decided that some of the structure/content in these surveys would be too "sensitive". As with the decision on replacing three villages, a compromise had to be made to continue with the research, and so the village surveys (though already translated and approved by the China IRB at that time) were not used.

[3] See www.ifad.org/mpat for more information. At the time of the Summer 2013 survey work IFAD was finalizing MPAT and so we used the (then forthcoming) 2014 MPAT surveys for the data collection.

3. Data collection tools and methods

3.1 Household surveys

To collect data on demographics, livelihoods, assets, access to social services, and a host of other variables which were thought to be potentially relevant with regard to households water treatment (HWT) beliefs and behaviors, this study used MPAT household surveys (Cohen, 2009, Cohen, 2010, IFAD, 2014). MPAT surveys collect a mix of quantitative and qualitative data, on categorical and continuous scales, related to key dimensions of rural poverty (e.g., food security, water, health, sanitation, housing, education, agricultural assets) and were originally developed in China and India; thus they were particularly appropriate for this study. These components and subcomponents are outlined in Figure 4. The MPAT surveys (and additional questions) are presented in English and Chinese in Appendix I.

The MPAT surveys also collect data at the village level, from village leaders, healthcare staff and teachers. These data are combined with the household data to calculate a number of subcomponents which feed into 10 components. As mentioned above, unfortunately it was not possible to use the MPAT Village surveys, so some of the subcomponents could not be calculated. Similarly, as described below, the CCDC insisted on deleting/censoring a number of the survey questions, meaning a few other MPAT subcomponents could not be fully calculated due to missing data.

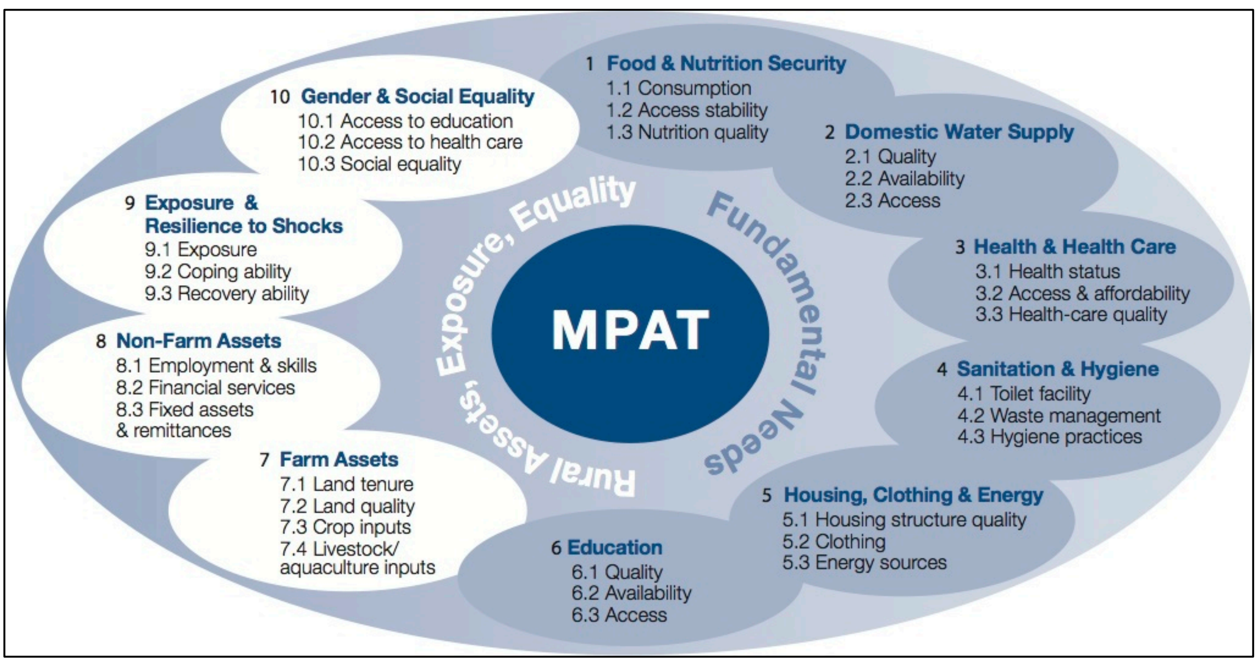


Figure 4: MPAT indicators (source: www.ifad.org/mpat).

Additional survey questions were designed, field-tested, and added to the end of the MPAT surveys. Specifically, we augmented the existing survey with additional questions to collect sufficient data on water-related beliefs and behaviors as well as boiling behaviors. The questions related to water-related behaviors and beliefs were created based in part on Mosler's (2012) survey items on this subject (with additional input from: Huber et al., 2011). Their approach is to use questions on behaviors and beliefs about drinking water and drinking water treatment to collect data on five categories of beliefs, namely: Risk, Attitude, Normative, Ability and Maintenance beliefs (Huber et al., 2011), and we felt this general approach would be useful for our research.

These survey questions were augmented with additional data on household fuel consumption (self-report: type and source of fuel, and approximate quantity used per day, cost of fuel, time needed to collect, combusted indoors or outdoors, etc.). Additional water and sanitation related questions already developed and tested in rural Kenya (in 2011 by Cohen when working with the NGO, Nuru International) were piloted as well.

I also spent a good deal of time thinking about the most appropriate/logical ordering of these new questions, considering the need for a logical flow (grouping similar questions together to make it easier for respondents) and placing the more sensitive questions toward the end of the set (see Figure 5). Ideally, we would have tested multiple versions of these new survey questions in different orders/grouping, but as it was the general piloting and revision of the new survey questions was quite time consuming (discussed below) so this was not feasible.

Figure 5: Ordering questions to create the first-draft of the new survey items on drinking water and fuel use

3.2 Water sampling and analysis

This baseline socioeconomic data on livelihoods, poverty and HWT practices and behaviors/beliefs gathered from the surveys was complemented with drinking water quality analysis (microbial at the household level, and physico-chemical analysis at the village level).

3.2.1 Microbial water quality analysis at the household level

Household drinking water quality was assessed by asking survey respondents (at the completion of the surveys) to provide enumerators a cup of water as if they, the respondent, would drink it (not as they would prepare it for guests). A sample was collected from this drinking water and was then taken in a sterile container, on ice, to the County CCDC laboratory for analysis (ideally, within six hours from when the sample was collected).

In China the method of microbial analysis of drinking water is standardized across the country for all CCDC labs; while I had originally hoped to test for *E.Coli* (using membrane filtration), if we wanted certified water quality results we would have to use the existing CCDC protocol.

The CCDC uses the World Health Organization (WHO) protocol for Multiple Tube Fermentation: "In the multiple-tube method, a series of tubes containing a suitable selective broth culture medium is inoculated with test portions of a water sample. After a specified incubation time at a given temperature, each tube showing gas formation is regarded as "presumptive positive" since the gas indicates the possible presence of coliforms. However, gas may also be produced by other organisms, and so a subsequent confirmatory test is essential. The two tests are known respectively as the presumptive test and the confirmatory test. For the confirmatory test, a more selective culture medium is inoculated with material taken from the positive tubes. After an appropriate incubation time, the tubes are examined for gas formation as before. The most probable number (MPN) of bacteria present can then be estimated from the number of tubes inoculated and the number of positive tubes obtained in the confirmatory test, using specially devised statistical tables. This technique is known as the MPN method" (WHO, 1997: 189).

Thus, CCDC staff were responsible for measuring and quantifying the degree of microbial contamination using Multiple Tube Fermentation to quantify the following water quality indicators: Total Bacterial Count, Total Coliforms, and Thermotolerant Coliforms (TTC). While Total Bacterial Count and Total Coliforms are indicators of microbial contamination in the water, TTC originate primarily from the digestive systems of humans and animals, indicating fecal contamination in the water.

3.2.2 Physicochemical water quality analysis at the village/source level

In each of the 15 villages, water samples were collected from the primary source water (i.e., the primary drinking water source for the village, whether it be groundwater, surface water, or water from a small-scale water treatment plant). For each village's water source, a few physicochemical parameters (listed below) were analyzed. In cases where there was no primary source (e.g., in villages where most households use rainwater harvesting, or in which there are multiple primary sources), three samples were collected, combined, and analyzed. The purpose of these measurements was to understand the efficacy of different treatment methods, and because boiling only inactivates pathogens it was important to have a basic understanding of the level of potential exposure to chemical contaminants in source water.

For the summer data collection CCDC was responsible for collecting these samples and analyzing them. For the winter data collection CCDC once again collected and analyzed samples, and I was also given permission to collect water samples and analyze them for additional contaminants.

The following parameters were measured by County CCDC during the Summer of 2013, and then again in December 2013 and January 2014[4]:

- pH
- Turbidity
- Total hardness
- Fluoride (F-)
- Nitrate (NO3-)
- Chloride (Cl-)
- Iron (Fe)
- Sulfate (SO4)

In addition, I complemented this analysis by assessing the following parameters (using a Hach CEL/850 Basic Drinking Water Laboratory) during the winter data collection from four villages:

- Iron, Fe total (0-3.0 mg/L)
- Nitrite, Low Range (0-0.35 mg/L No2-N)
- Nitrate, High Range (0-30 mg/L NO3-N)
- Phosphate (0-2.50 mg/L PO4^3-)
- Sulfate (0-70mg/L SO4)
- Aluminum (0-0.80 mg/L Al)

3.3 Household Air Pollution and boiling measurement

Given the high expected prevalence of households boiling their drinking water, as mentioned above I added questions on the types of fuels used to boil water, the quantities used, and the

[4] During the planning stage I had requested that we also test for benzene, bromine, cyanide, hexane, mercury, perchlorate, and zinc and while the NCRWSTG Director agreed, unfortunately we were not able to work with the Provincial and County CCDC offices to do this.

frequency of use. The goal of these questions was to try and get a better sense of household air pollution (HAP) exposure from boiling specifically.

Unfortunately, as is apparent based on a number of studies (e.g., Masera et al., 2000, Jin et al., 2006, Zhang and Smith, 2007, Baumgartner et al., 2011), it is incredibly challenging to understand which fuels household use for which applications (e.g., cooking, heating, boiling), and at which times, and what the associated costs and health impacts are.

In order to corroborate this self-report data from the surveys, I chose to use remote temperature sensors to help determine the likely accuracy of the survey data. Stove Use Monitoring System (SUMS) temperature loggers/sensors were developed for improved-stoves research (Ruiz-Mercado et al., 2008, Ruiz-Mercado et al., 2012)[5], but for this research we affixed them to water pots and electric kettles in a subsample of households. Because the SUMS cost ~60 USD each, this limited the extent of their use.

Originally, I planned to use the SUMS in ~10% of the sample households (n=45) across three or four villages, randomly selected from each of the two counties during the Summer 2013 data collection as well as the Winter data collection. Due to delays and other issues, this work was done only in December and January.

Within these villages, SUMS were installed on water kettles and pots used for boiling water in households which regularly boiled their water and who agreed to allow us to place the SUMS on the pot or kettle. The sensors were left on the kettles for at least 72 hours and were pre-programmed to start logging data at the same time (midnight on the first day they were placed) in order to track the frequency and duration of boiling. The SUMS units record the temperature every minute (with a range of 0°C to 125°C). This may be the first study of its kind to use these sensors on water kettles and pots instead of stoves.

3.4 Equipment Costs

Household surveys, water sample collection, and microbial analysis were undertaken by the NCRWSTG and CCDC following training. For the winter village-level water quality analysis, I used a Hach CEL/850 Basic Drinking Water Laboratory (USD 2,138 + shipping to China, paid via my EPA STAR research account). I also purchased 20 SUMS iButtons, as well a probe to transfer the data to a computer and heat tape (USD 1,128 China paid via my EPA STAR research account) – at study completion, I donated the SUMS iButtons to the NCRWSTG for use in their future research.

[5] See also: http://www.berkeleyair.com/products-and-services/instrument-services/78-sums for more information.

4. Spring/Summer 2013: Data collection chronology

4.1 Presenting the research plan to Guangxi Province CCDC staff

On June 5th, 2013, shortly after moving to Nanning (where I was based for the summer data collection) I presented the Plan of Work for our research to the "Institute of Environmental Health and Endemic Disease Control", directed by Zhong Gemei, a unit of the Guangxi Zhuang Automonous Region Center for Disease Prevention and Control.

While Director Zhong had already been included in the planning process and the March scoping mission, the point of this workshop/presentation was to more thoroughly introduce the project to the rest of her staff as well as other Guangxi Province CCDC officials – see Figure 6.

Figure 6: Presenting the research plan (left) & group photo with Director Zhong Gemei (right)

4.2 Piloting the newly developed survey questions

The rest of the month of June, 2013, was used to finalize preparations for enumerator training and data collection, and to pilot, revise, and finalize the supplementary household survey questions. While the MPAT Household surveys had already gone through extensive development and testing in a number of countries including China, the newly developed survey questions for this research project were field tested and revised before being used in the full study.

As with many other aspects of this research, I had hoped for more time, and more iterations, to pilot and revise these new questions, but in the end we only completed two iterations. The questions were originally developed ahead of the March/April scoping missions to Guangxi and Shaanxi and were then shared with the CCDC counterparts so that they could test them in the field and provide feedback. Unfortunately, this did not happen, and we got very little feedback from that early round.[6] As such, we worked as a group (the Nanning-based CCDC staff who had attended the workshop on June 5th) to further develop and refine the new survey questions, in particular focusing on the translation so as to arrive at wording which would be readily intelligible to respondents.

On June 13th, following a brief training I provided on enumeration, we travelled to the outskirts of Nanning (~60 minutes driving distance from the Nanning CCDC headquarters) to a village in a county which would not be included in the research. We split into a few teams and, after explaining clearly that this was just for practice and that the data would not be stored or used in any way, we practiced using the surveys (with a focus on how the skip logic functioned) with willing respondents (see Figure 7). We then returned to Nanning and worked together as a group using a projector to edit and improve the questions based on discussions of the issues encountered during the day's testing (far right image, Figure 7).

Figure 7: Piloting new survey questions, round one (left and center) & making revisions in Nanning (right)

The following day, June 14th, we met in the morning at the Nanning CCDC headquarters and spent more time finalizing the new version of the surveys. We then travelled to a different area, also relatively close to Nanning to pilot the questions in a different village (see Figure 8). This second round was very helpful and we found that the improvements/edits from the previous round worked well, and the surveys were now more easily understood, with well-functioning skip-logic and more readily intelligible question wording. That said, we still discovered a number of areas

[6] This is partially explained when considering that this type/style of research is not commonly practiced in China, and when the request to do early field testing was made, the Province CCDC staff did not consider it a priority.

that required further revision and improvement. At the end of the day we met again as a group to share notes and observations and agree on final revisions to the survey questions.

Figure 8: Piloting the new survey questions, round two

4.3 Unanticipated changes to the summer research plans and timeline

The original plan for the summer data collection was to use June to prepare, practice and finalize the data collection protocols, and then to start with enumerator training and data collection in early July. Initially, more than seven weeks were allocated for data collection. Unfortunately, the timeline for data collection had to be significantly revised and delayed; the combined result was that I was unable to visit each of the 15 villages along with the enumerator teams as I had originally planned (so as to better understand the situation in each village and to provide direct-supervision for the data collection efforts). This also meant that I was unable to use the SUMS or collect water samples from each village for physicochemical analysis. A rough chronology of the primary difficulties and obstacles is as follows.

Enumerator training for County B CCDC staff began on-schedule on July 2nd. Director Tao arranged for Luo Qing (one of his staff who was tasked with assisting me with the research management process) to fly to Nanning and accompany me to County B. In addition, Director Zhong arranged (at my request) for three of her staff (Huang, Wei, and Li) to come as well. I asked that they join since, at that time, I assumed I would later train them to assist with the data entry in Nanning; as such, I wanted them to attend the training so they would be very familiar with the surveys and thus better able to identify errors and logical inconsistencies in the completed surveys we would later review during the quality control process prior to data entry.

I had originally requested a week-long training (including field practice and evaluation), but because the CCDC were accustomed to one or two-day trainings for survey work we compromised on a three-day training schedule, after which the County B county staff would immediately start the survey work with me accompanying them to all villages to provide support as needed (I would of course not visit any of the selected households until after all data was collected, if at all).

However, at the end of training day two (July 3rd) the county director decided to suspend the training and did not give clear reason why. Director Tao called from Beijing to speak with him but he would not change his mind (at that time Director Zhong was in Japan for a conference, we reached her by phone but she too was unable to convince the county director to resume with the training). Consequently, myself, Luo Qing, and the rest of the Nanning CCDC team, returned to Nanning on July 4th. I would later learn there were, most likely, three related reasons for this last-minute suspension of the training:

1. General caution and concern due to the 2012 Golden Rice "scandal"[7] involving CCDC and Tufts University,
2. At the start of the training, the Beijing CCDC staff involved in the project preparation had not yet completed the necessary permissions/paperwork,
3. Similarly, Beijing had not completed a translation of my English-language Plan of Work, and so had not shared a Chinese-language version with the county director; as such, neither he nor his staff understand why we were asking some of the household survey questions (e.g., on debt, or sanitation, or education) when they understood this to be a project strictly concerning drinking water.

As such, the county director decided to err on the side of caution and postpone the training until the paperwork and permissions were fully in order. At the start of the training on July 2nd I was of course unaware of these issues, but at the beginning of the first day of training I had (as I have done in past situations) provided the county staff a general introduction to the larger project so that they might understand more clearly why we were collecting this data and the importance of their role generally – but clearly in face of the issues outlined above this was insufficient.

When we returned to Nanning my colleagues in Beijing assured me they would work as quickly as possible to get the paperwork finished. Slowly, it also became clear to me that a big part of the problem was that the County CCDC were not researchers and thus in the past the survey work they had done had been completed in order to address monitoring and reporting objectives only. As such, it was understandably difficult for them to imagine why a research project about water might also involved data collection around issues such as health or agriculture, for example.

In order to try and address this knowledge-gap and some of the concerns of the County B director, I quickly prepared a three-page document which gave a very general explanation of the research and why it was important to measure indicators that did not appear to be immediately linked to water. I also explained the potential linkages between drinking water and MPAT's various

[7] http://www.nature.com/news/china-sacks-officials-over-golden-rice-controversy-1.11998

components. This short document was quickly translated to Chinese and shared with the county director and then used as part of the subsequent training introductions.

These delays were particularly challenging because County B was scheduled to begin another survey for another project starting July 18th, and thus if the delay was too long the window would be too short for them to complete the training and then survey the seven villages for our study (before July 18th that is). To complicate matters further, shortly after returning to Nanning the Director Zhong's division had to respond to an emergency water pollution crisis[8] (which made domestic and international headlines on July 6th) due to water contamination from illegal mining operations in northern Guangxi. Director Zhong returned from Japan on July 7th and immediately traveled to the region where the pollution occurred. Water samples were collected and sent to the Nanning CCDC laboratories for analysis while Director Zhong stayed in the region. This delayed our research plans further since Director Zhong and her staff were, understandably, focused entirely on addressing this emergency. However, in hindsight, this crisis likely did not contribute to the delay of our research because during the week of July 8th I was told that the necessary documents would not be finished in time for us to resume work in County B that week, and so it became very unlikely we would have enough time to complete the surveys before July 18th (in spite of the generous offer of the County B CCDC to work over the weekends if needed).

In the course of the final preparation of permissions/documents, the Beijing IRB requested that we delete/censor some of the survey questions (related to household debt and land tenure, in particular)[9]. In addition, they wanted to delete most of the questions related to social and gender equality (on both the household and village surveys). I complied because refusing to do so would mean the protocol would not be approved.

Due to these delays, it was decided to shift the County B training to August and do the County A training first. The County A training was scheduled to start on Monday July 22nd, but on Friday the 19th it was abruptly cancelled due to an unspecified "emergency" in County A and rescheduled for July 29th. On July 25th, a few days before the County A training was to begin, staff from County A made it clear that they were unwilling to survey three of the randomly sampled villages and so we used replacement villages (discussed above on page 29, see also Table 2). In addition, at the insistence of the County A director/staff, a few more survey questions were deleted/censored (they also requested to cancel the physicochemical water testing for all villages, but fortunately this was resolved). During this time, it was also suggested that due to unspecified government concerns I would not be permitted to visit any of the villages in either county. On top of all this, shortly before the County A training was to finally begin, they decided they would

[8]These are three examples of the related media coverage: http://www.chinadaily.com.cn/china/2013-07/06/content_16741633.htm, http://www.businessweek.com/articles/2013-07-08/illegal-mines-taint-river-in-southern-china, and http://usa.chinadaily.com.cn/china/2013-07/08/content_16744075.htm

[9] This was also surprising because I had already used similar survey items for a 2009 project in particularly politically-sensitive areas of rural Gansu Province (though that project was approved by the Chinese Ministry of Finance).

not use the MPAT Village surveys (even though the CCDC IRB had already approved a slightly censored version). Training in County A did finally begin at the end of July.[10]

4.4 Summer 2013: Enumerator Training

4.4.1 County A training

Enumerator training in County A was conducted over three days from July 29th to the 31st. On the first day, County A CCDC Director Wang opened the session and explained the general purpose and importance of the research project, followed by a more in-depth introduction by myself and Luo Qing - see Figure 9.

Figure 9: County A training: Director Wang opening session (left) and Cohen explaining the surveys (right)

The enumerator training approach was derived from the one I developed while working on the MPAT project. Briefly, this involved going through all the survey questions as a group to make

[10] This was a challenging period for me. As each obstacle presented itself I did my best to work though it and preserve the integrity of the research design. To this end, I wrote multiple revised timelines and modified the plan of work to try and address these cancellations and revisions. It was especially frustrating to be unable to follow through with research plans that were approximately two years in the making, and more generally it was challenging to not have the opportunity to visit field sites and work at a reasonable pace to collect the research data. In hindsight, I believe many of these problems were due to a lack of advanced planning and communication between the different levels of the CCDC involved in this project. In particular, it became clear that while Beijing and the Province level CCDC staff involved generally understood the research design and the suggested data collection methods, the County CCDC offices did not, and were only informed shortly before field work was to begin. Reflecting on the larger context, all of this took place in the context of a politically sensitive collaboration (foreigner from a US university) on a highly sensitive issue (water quality). Under such atypical circumstances and with a severely limited understanding of the bigger picture, the county CCDC staff's hesitancy to participate in a study so different from their usual work is certainly understandable.

sure they were sufficiently clear and then reviewing how the questions should be asked and how the surveys should be marked. Supplementary materials were provided to guide trainees through the steps involved in the survey process and to explain how different circumstances should be addressed for each question. The interested reader may consult the MPAT User's Guide (IFAD, 2014) which provides detailed training resources.

Once trainees were sufficiently familiar with the surveys and how to use them, we conducted role-playing exercises (e.g., one person as the enumerator and one as the respondent) to further demonstrate how the surveys were to be used. We also broke into pairs to allow them to practice more, with support provided as needed – see Figure 10.

Figure 10: County A County training day two: Reviewing the surveys (left) and practicing in pairs (right)

When the classroom section of the training was completed, we arranged to visit a nearby village (one that had not been randomly selected for participation in the research) to allow trainees the opportunity to practice using the surveys with "real" households/respondents. In order to simulate a would-be typical day in the field, we had the teams go through all the procedures as if they were already starting to collect research data (i.e., randomly selecting households with the village leader, administering the surveys, collecting water samples) – see Figure 11 and Figure 12. This also provided an important opportunity for us to agree on a standardized method for using codes to ensure that household surveys and drinking water samples remained linked together anonymously.

Figure 11: County A training day three: Distributing water sample containers (left) and walking to the village (right)

Figure 12: County A training day three: Huang, Luo, Wei, Cohen (left) and typical household kitchen (right)

The collected drinking water samples from each household were stored on ice in coolers for transport back to the county CCDC laboratory – see left side of Figure 13. Because the county CCDC staff had extensive experience collecting and analyzing drinking water samples, I did not have train them for this part of the data collection, though I did train them to collect drinking water samples from respondents as if they, the respondent, were going to drink it. I also made sure I fully understood their sample storage, transport, and analysis protocols – which was partially done by visiting their county laboratories and speaking with technicians – right side of Figure 13.

Figure 13: County A training day three: Drinking water sample storage (left) and lab analysis (right)

At the end of the third day we met as a group back at the county CCDC offices where the training began. As a group (Figure 15), we reviewed common errors made and common problems encountered. In addition, I felt that the importance of the random sampling of households was perhaps not yet sufficiently clear and so I created and gave a short presentation on different sampling approaches at the village level with a focus on the importance and benefits of our method, including examples from my past work in rural Kenya and Bangladesh – see Figure 14.

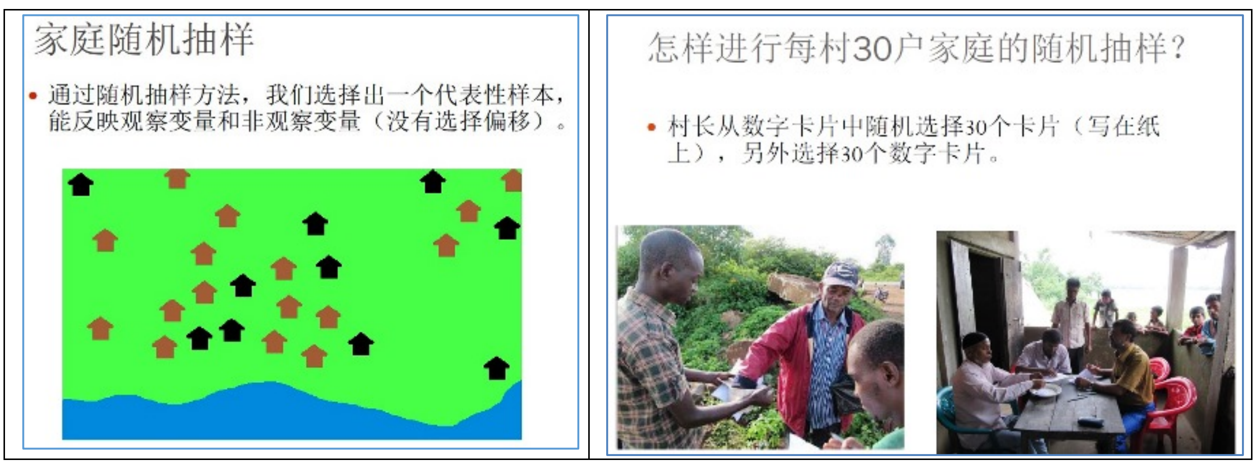


Figure 14: County A training day three: Screenshots from PPT on Household Random Sampling

Figure 15: County A training day three: Group photo

4.4.2 County B training

As discussed above, the training for County B started on July 2nd (left side of Figure 16), was suspended the evening of July 3rd, and recommenced August 5th (right side of Figure 16). The procedure was much the same as for County A, the difference being that because the County B enumerators had already completed two full days of training less time was spent on the initial part of the training.

Figure 16: County B training: Initial start date, July 2 (left) and recommencement, Aug 5 (right)

On the second day of training (August 6th) we finished reviewing the surveys and went over those questions which were particularly challenging under different circumstances. After a role-playing demonstration, the trainees practiced in pairs and then during the afternoon we went to a nearby village (as with County A, selecting a village that had not been randomly selected to participate in the study) to simulate a typical day of data collection and allow enumerators to practice using the surveys – see Figure 17.

Figure 17: County B training day two: Role playing and classroom practice (left) and field practice (right)

Figure 18: County B training day two: Field practice in the village (left) and collecting drinking water samples (right)

On the morning of the third day of training (August 7th), we reviewed common errors and issues encountered during the field practice and I closed the session with a presentation on the importance of randomly selecting households at the village level – see Figure 19.

Figure 19: County B training day three: Presentation on random sampling of households and group photo

4.5 Summer 2013 data collection

4.5.1 Households surveys

All the surveys were administered between August 1st 2013 and August 19th 2013. The county CCDC teams completed between 24 and 35 surveys per day, with a total of 450 households surveyed. The average survey duration for the entire HH survey was 40.8 minutes (sd = 7.53 min). The average survey duration for the MPAT portion was 26 minutes (SD = 6.3 minutes) and 14.9 minutes for the additional survey questions (SD = 5 minutes). In an effort to help ensure adherence to the sampling strategy, we asked the enumerator team supervisors to take pictures of the household random sampling process with village leaders in each village (as well as pictures related to drinking water and household cooking) – see Figure 20.


Figure 20: Random household sampling with village leaders in two villages (photographs taken by CCDC staff)

4.5.2 Water samples from households and villages

After finishing the household surveys, enumerators collected a drinking water sample from each household. In order to maintain the anonymity of the data collection, an arbitrary code was marked on the top right-hand corner of each survey and the same number was marked on the sampling container. Multiple Tube Fermentation results were printed and certified by the county CCDC laboratories and affixed to the last page of the household survey.

In the interests of standardization, it was agreed that the CCDC staff in both counties would use the official CCDC methods for sampling primary drinking water sources in the villages (versus collecting composite water samples as I had suggested – but which could not be official certified by their laboratories if used). Samples for physicochemical analyses were sent to the Guangxi Province labs in Nanning.

5. Summer 2013 data entry and quality control

5.1 Data Entry Training, Beijing

I had planned to have the data quality control and data entry done in Nanning by CCDC staff based there, so that the surveys could be sent village-by-village from the field sites to Nanning as they were completed. This would have allowed us to identify errors early and provide feedback to specific enumerators so they could correct such errors before they continued administering surveys in other villages. That is, by quickly reviewing the completed surveys from the first village surveyed we could have identified common errors and provided feedback to the specific enumerators so they would not repeat the errors in subsequent villages.

The Guangxi CCDC were unable to allocate sufficient staff for this purpose, and so at the suggestion of Director Tao we shifted the data quality control and entry to the NCRWSTG offices in Beijing. Fortunately, thanks to the training there were relatively few enumerator errors.

I travelled to Beijing to train the NCRWSTG staff using the "check-score-code" method I developed for MPAT (IFAD, 2014). This method provides a two-stage process for checking and double-checking the quality of the survey data for accuracy/legibility and logical consistency. This is then followed by the actual coding of the data and entry into spreadsheet templates I created. I also assigned code numbers to all the staff involved in the data entry work, so that just as for the codes assigned to each enumerator and supervisor, it was relatively straightforward to identify who was responsible for errors and at which stage of the data collect, screening, and entry steps. Pictures from the first two days of training are shown in Figure 21 and Figure 22 (Luo Qing supervised the third day of training).

Figure 21: August 14th: Training NCRWSTG staff on quality control and data entry procedures for the household surveys (NCRWSTG headquarters, Beijing)

Figure 22: August 15th: Day two of quality control and data entry training - completed survey (left) and staff working on the check-score-code method (right)

5.2 Quality control, data entry, and data cleaning

5.2.1 Initial data checking and cleaning (October & November, 2013)

NCRSWTG staff checked and entered the survey data during September and October, 2013. After the data entry was concluded in Beijing, under the supervision of Luo Qing, the results were emailed to me in Excel spreadsheets.

I checked each variable individually for data entry errors and potential outliers during October and November, 2013. I created two tables for each county, in order to list all surveys with potential data problems. I emailed these tables to Luo Qing who then consulted the hard-copy versions to clarify potential inaccuracies and correct data entry mistakes. Luo Qing added comments/feedback to the tables explaining for each item what the issue, if any, was (e.g., data entry error, possible outlier, enumerator mistake) and I used the feedback to clean the data in Excel.[11]

[11] On November 22nd my laptop was stolen. Because my most recent back-up was three weeks old I had to re-check and re-clean the data; while time-consuming, this provided a good opportunity to double-check many of these issues.

5.2.2 Spot-checking the surveys against data in the spreadsheets (December, 2013)

In early December, 2013, when I returned to China (for the winter data collection), I first spent a few days in Beijing working with Luo Qing to do one last check of the data entry quality with the hard-copies of the surveys (Figure 23) and water analysis results (Figure 24). We randomly selected two surveys from each of the fifteen villages (6.6% of the entire sample) and compared the data from the surveys with the final version in our spreadsheets (i.e., after our quality control and data cleaning).

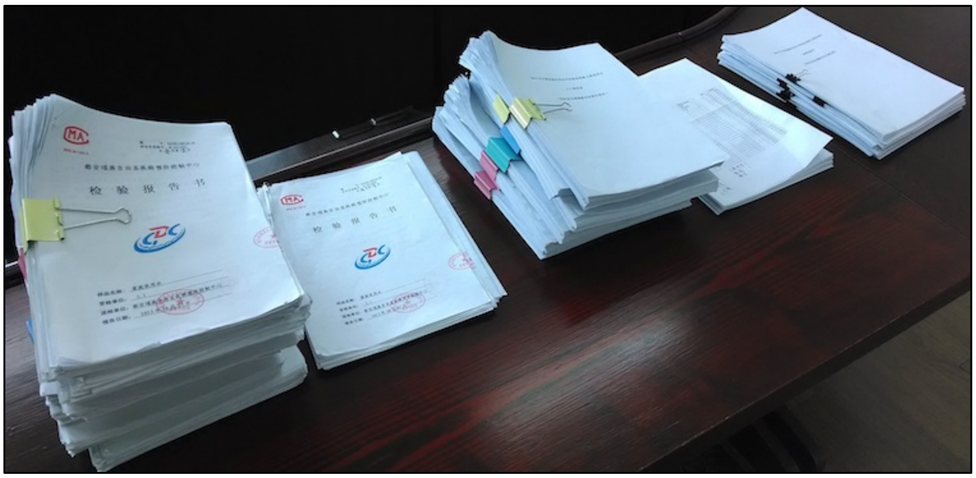


Figure 23: Surveys from County A (left side) and photocopied surveys from County B (right side)

Figure 24: Cover of certified microbial analysis results for one household (left) and close-up of full results (right)

Out of thirty randomly selected surveys only six data entry errors were found, two of which were due to the incorrect calculation of the total survey time duration. Thus, the error rate (out of 132 variables per survey [counting only data that could be used for analysis, not counting data such as “enumerator supervisor code” and the like] was 0.15% (132 variables per survey, 30 surveys, yields 6/3960=0.001515). This indicated that the quality control and data entry were done to a high standard, and it was not necessary to re-check additional surveys. In addition, I reviewed all the village-level water analysis results to ensure that the data was properly recorded in the spreadsheets (which it was).

6. Selection criteria for identifying 2013-2014 winter villages

In the original Plan of Work for this research, in order to control for seasonality and understand how HWT use and related behaviors change during the cold/dry season, I proposed to collect data from the entire sample during the winter (revisiting all 15 villages). However, as the time for winter data collection approached, the county CCDC directors indicated that they were concerned about the costs and time that would be required as well as the burden this would add to their existing work load for that time of year.

As such, I agreed to a scale-back of the winter data collection from 15 villages to four (two villages in each county). Though sampling only four villages would be problematic with regard to the winter study's power, this was preferable to not collecting any winter data (and I wanted to use the SUMS iButtons since I was not able to during the summer).

Rather than selecting four villages randomly (since the sample size would be too small in any case), in the interests of better understanding some of the key research questions, I used the summer data to identify villages with relatively high proportions of boiling and untreated water consumption (using multiple, overlapping, survey items). Using this primary approach, I chose villages three and six in County A, and villages nine and 10 in County B.

7. Winter 2013-2014: Data collection chronology

For December and January (2013-2014), we administered only the new household survey questions (#74-107), collected household drinking water samples, used SUMS temperature sensors in households who boiled and consented, and collected village-level samples for physicochemical analysis. After a few days in Beijing, in mid December, 2013, I traveled back to Guangxi to meet with the Provincial CCDC staff in Nanning to organize finalize preparations for our field work.

7.1 SUMS temperature sensors programing and protocol

Based on the schedules of the staff in each county, we first went to County A, visiting village three and then village six; we then went to County B, visiting village nine followed by village 10. There were 14 households that met eligibility criteria for using the SUMS in village three, eight households in village six, ten households in village nine, and 14 in village 10, for a total of 46 households. This was fortunate since our objective had been to obtain SUMS data from at least 10% of our entire summer sample size (450 households).

The SUMS iButtons were all labeled with a unique number and then pre-programmed (Figure 25) to start logging data at just before midnight at the end of the day they were taped to the kettles and pots. They were not collected until a minimum of 72 hours had passed, so that for every household we had a full 72 hour's worth of data over the same time period (12:00 in the morning to 23:59 on the third day). Specifically, the SUMS were programmed to take a temperature reading once every 60 seconds for the full 72 hour period (at this resolution they could log data for up to five days). Once they were collected from a given village, all the data was downloaded and the memories were reset so they could be programmed for use in the next village.

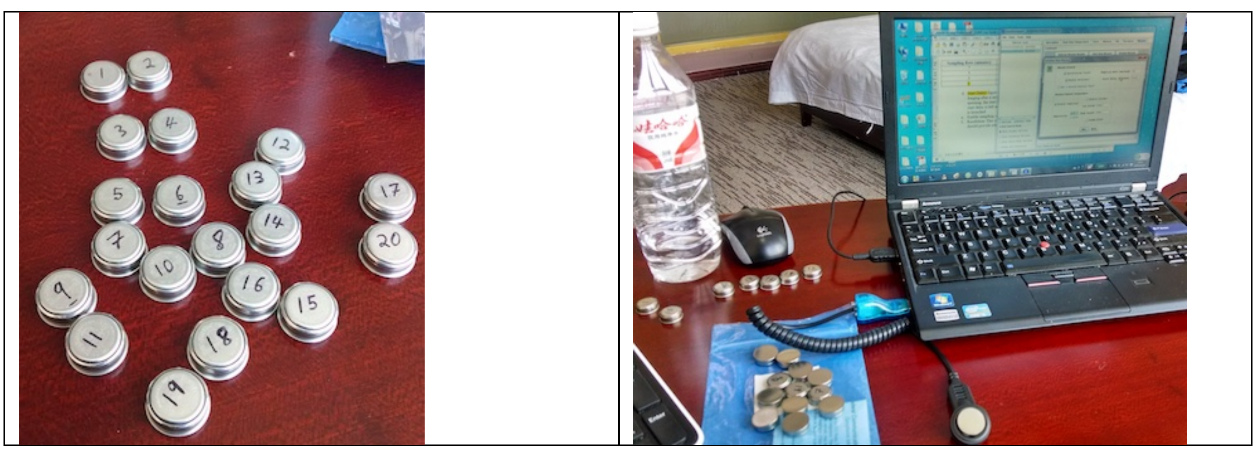


Figure 25: Labeling and programming SUMS temperature sensors (photographs at hotel in County A)

7.2 Overview of data collection: Surveys, water samples and SUMS

As with the summer data collection, the village leaders were contacted prior to our arrival and were waiting for us when we arrived in the villages. We met with them and cut out a number tabs corresponding to the number of households in the village and then asked the village leader to randomly select 30 (our desired sample) followed by an additional 10, in the event of non-response. As during the summer data collection, village residents were not discouraged from watching this process, since this only helped to further clarify to those involved that this was a random process and they could later tell any sampled households that they saw the random selection process. Once the households were all collected, the village leader explained where the households were and accompanied the teams at times if the locations were not clear.

Since we were using household lists based on the most recent census, we knew the locations of the selected households as well as the head of the household's name. This information, linking the head of the household's name to the household code, was kept on a separate sheet of paper and linked only by the arbitrary household code used. Once the surveys were administered, this separate piece of paper was discarded so that it was no longer possible to link a given survey form to a given household (though of course it was still linked to a given village). The only exception was for those households where we left a SUMS unit, and in these cases we explained to them that the survey and SUMS and their household name/code would remain linked until we returned (usually four days after the survey) to collect the SUMS from their home, at that time we would then discard the paper linking the surveys and SUMS to their specific home.

The administration of the household survey questions, using only the custom-developed questions, #74-107, and collection of drinking water samples from each household was done in the same fashion as in the summer. The average survey duration was 10.4 minutes (SD = 4.1 minutes). See Table 4 for an overview of the survey administration and SUMS data collection.

Table 4: Schedule of 2013-2014 Winter data collection and SUMS placement and collection

M	T	W	T	F	S	S
Dec 16, 2013	17	18	19	20 A3: P, S	21 A3	22 A3
23 A3	24 A3: C A6: P, S	25 A6	26 A6	27 A6	28 A6: C	29
30 B9: P, S	31 B9	Jan 1, 2014 B9	2 B9	3 B9: C B10: P, S	4 B10	5 B10
6 B10	7 B10: C	8	9	10	11	12

P = place SUMS | C = collect SUMS | A = County A County | B = County B County | # after A or B = village #
Gray-shaded cells are days when SUMS were logging data (72h per village) | S = Household survey administered

For this winter data collection, we used a consent form which also discussed the potential request to use a SUMS if the household regularly boiled water. I accompanied each team to the villages and we then split into two teams to cover different geographical areas of the villages. I only visited households after the household surveys were completed. I trained Mr. Huang (Guangxi Province CCDC officer) on how to affix the SUMS to kettles/pots using the heat-resistant tape and instructed him to take a photograph (with his cell phone) of each SUMS once it was affixed (since he accompanied me, as well as Luo Qing, to all four of the villages). I did the same, and this helped ensure that we knew which type of boiling vessel the SUMS were logging data from. In all four villages Mr. Huang and I followed the same procedure with regard to the SUMS: namely, once a household survey was completed, if the household regularly boiled their water and agreed to the SUMS placement, we would give them a short briefing and then affix the SUMS and take a picture before thanking them and leaving the households[12].

Every household we asked agreed to let us place the sensor on their kettle or pot. The only concern voiced was that it would fall off and, if lost, they would be responsible for it. For these few households we explained that it would be securely taped (using a special heat-resistant tape which would not damage their pot or kettle) and that if it did fall off and/or was lost they would not be held responsible. By the end of our data collection we did not lose any of the sensors, though one of them (in village three) did fall off after the first day.

The county CCDC staff collected household drinking water samples as well as samples from each village's primary drinking water source for physicochemical analysis (using the same approach as describe for the summer data collection). I also collected village-level samples to conduct a parallel analysis using the Hach water testing kit. Photographs from the data collection in these four villages are provided below.

[12] **Note:** with regard to potential bias introduced or boiling behavior change due to the use of the SUMS, it is unlikely that that the SUMS induced any significant behavior change. This is primarily because we were not asking households to change their behaviors/habits in any way, and since boiled water was/is such a central part of their daily lives, not boiling water was not a behavior that would have been chosen simply in reaction to the presence of the SUMS.

7.3 Photographs from the four study villages

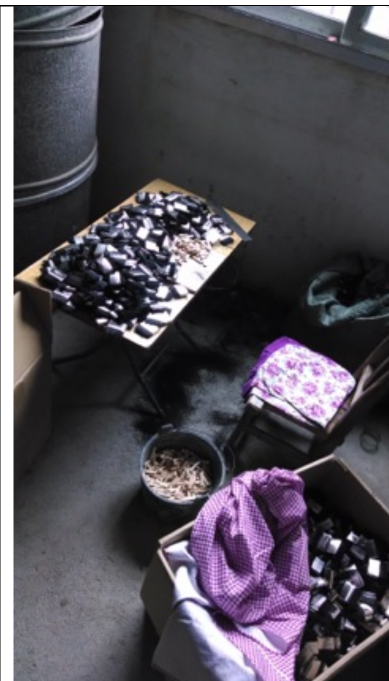
Photographs from Village 3





Photographs from Village 6

Photographs from Village 9



Photographs from Village 10

8. Winter 2013-2014 data entry & quality control

8.1 Data entry and quality control - Beijing

The procedures used for the summer data were again used for the winter data (with NCRWSTG staff in Beijing).

8.2 Water sample analyses

The procedures for the summer household and village level water sample analyses were again used by the CCDC for the winter data. For the village samples I collected, I conducted the bulk of the analyses at my hotel in Nanning (Figure 26) while waiting for the SUMS to collect 72 hours of data, as well as in county hotels. Glassware was cleaned by double-rinsing, first with distilled water followed by a rinse with deionized water. The reagents used for the nitrogen analysis contained cadmium, and thus the water/samples from those tests were saved in a glass thermos and given to the CCDC laboratory in Nanning in early January 2014 for hazardous waste disposal.

Figure 26: Analyzing village water samples with Hach CEL/850 portable laboratory (Nanning hotel room)

9. Groundtruthing and qualitative feedback

After I completed the initial data analyses and modeling I shared a draft of the initial results (and explanation of the statistical methods I used) with NCRWSTG colleagues in Beijing as well as with Director Zhong in Nanning. In early November I traveled to Beijing to meet with NCRWSTG colleagues there to discuss these initial results. I then travelled, accompanied by Zhang Qi and Luo Qing of the NCRWSTG, to Nanning where we held a day-long Groundtruthing Meeting (originally planned for two days) on November 7th, 2014. This meeting was organized and hosted by Director Zhong and CCDC staff from both counties travelled to Nanning in order to attend.

The purpose of the meeting was for me to present the initial data analyses and results in order to get their feedback. In addition, in the course of the data analyses a number of questions around and this was an opportunity to get qualitative feedback from these CCDC colleagues with regard to hypothesized causal pathways behind the associations of note in my analyses. The meeting was incredibly helpful (Figure 27) see and the county staff as well as Nanning based staff helped clarify a number of points and provided suggestions for additional analyses which I subsequently investigated.

Figure 27: Presenting to Guangxi CCDC county and capital staff at the Groundtruthing Meeting in Nanning (2014)

Following the meeting, Zhang Qi, Luo Qing, and I returned to Beijing where we discussed further. In addition, I presented the initial results to Yang Zhenbo and some of his UNICEF colleagues at their Beijing offices. Their feedback was also helpful with regard to my additional analyses.

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Chapter III

Household Water Treatment Methods & Effectiveness

Chapter III: Table of Contents

1. Introduction[1]

> "**饮水消毒** 浅井水或经过沉淀过滤后的河，坑水，虽外观清彻透明，但往往含有病菌，若直接饮用，仍可能传播肠道传染病，所以要进行饮水消毒。煮沸是最简便的消毒方法，在开展饮水消毒工作中，首先要宣传不喝生水，喝开水。"
>
> **"Drinking water disinfection** Although water from shallow wells, river beds, or pools, may appear to be clear, it often contains bacteria which if consumed can result in the transmission of infectious enteric diseases; as such, drinking water should be disinfected. Boiling is the simplest method of disinfection, so when initiating drinking water treatment [education/training], above all promote the drinking of boiled water, not raw/untreated water."
>
> (编写组编, 1970: 88 [my translation]).

In China, as in many countries in Asia, there is a strong cultural preference for boiled drinking water, even if the water is no longer hot or warm. I tried to understand the historic roots of this cultural preference but was unable to find any articles, in Chinese or English, on the subject. While living in China in 2012-2013, I asked a Chinese anthropologist and historian about this and they too were unaware of any literature on the subject, but surprised that such an important aspect of Chinese society did not appear to have been studied or written about. Through these conversations and others, as well as Chinese literature searches, it seems that this preference may stem from China's tea-drinking history and culture; there is some limited, peripheral, discussion of this in the literature (Bodde, 1942).

Other literature suggests that boiling water as a deliberate form of water treatment may have been promoted during China's "cultural revolution" (1966-1976), when more than one million people were trained as "barefoot doctors" and tasked with providing rudimentary healthcare and preventative health education across rural China (Sidel 1972). A core part of their training was focused on environmental hygiene and "…drinking-water, handling nightsoil [the use of human and animal feces as fertilizer] properly, improving the structure of wells, lavatories, animal sheds, and stoves, and keeping houses clean" (Wen, 1974: 978).

In an effort to better understand the potential impact of these "barefoot doctors" on boiling's widespread use, I purchased an old medical manual that was published specifically for the "barefoot doctors" (编写组编, 1970). In the section on drinking water treatment, the opening paragraph makes it very clear that, above all else, the boiling of drinking water should be

[1] The material in this chapter was later revised and expanded for a paper I published in 2015, co-authored with Berkeley and CCDC colleagues; among the co-authors, only Prof. Ray and Prof. Colford had central roles with the analyses and writing of the paper (this is stated in the paper's "Authors Contributions" section, see: COHEN, A., TAO, Y., LUO, Q., ZHONG, G., ROMM, J., COLFORD, J. M., JR. & RAY, I. 2015. Microbiological Evaluation of Household Drinking Water Treatment in Rural China Shows Benefits of Electric Kettles: A Cross-Sectional Study. *PLoS ONE,* 10).

promoted (see the quote at the beginning of this section). This suggests that the widespread use of boiling in rural China may well be largely thanks to the influence of these "barefoot doctors."

Results from a nationwide 2006-2007 survey indicate ~85% of the rural population, ~607 million people, were regularly boiling their drinking water during that period, with 5% using some other household water treatment (HWT) method, and the remaining 10% not treating their water (Tao, 2009). Given the widespread cultural preference for water that has been boiled, many households do not consider boiling a form of water "treatment" (a perception that can translate to HWT underreporting if not controlled for in survey design).

The origins of basic water treatment methods like filtration are even less clear, though some evidence also points to early tea culture as an inspiration due to the importance of high-quality water for tea preparation: an ancient work on the subject recommends using a constantly-flowing stream and filtering the water with a bamboo sieve prior to use (田艺蘅, 1554). There may also be links to the historical focus on the importance of protected wells for drinking water, versus wells whose water was used for other purposes (谈大庆, 2001).

With regard to present rates of safe drinking water access, the few available national estimates vary widely, a problem partially due to different definitions (Yang et al., 2012). The most accurate, though somewhat outdated, estimate available is from the nationwide survey mentioned above, indicating that ~317 million rural Chinese lack access to safe water (Tao, 2009, Zhang et al., 2009). More recently, the Chinese Ministry of Environmental Protection estimated that across China some 280 million Chinese lack access to safe water (MoEP, 2013a, MoEP, 2013b).

The Joint Monitoring Program estimates that 85% of rural Chinese have access to an "improved" water source (56% have improved sanitation facilities), and ~97[2] million use "unimproved" sources (WHO/UNICEF, 2014). Though "improved" sources often have less fecal contamination than "unimproved" sources, they are not a reliable indicator of access to "safe" water (Bain et al., 2014). Indeed, based on region-specific data (Chen et al., 2011, Jin et al., 2009) as well as national estimates (Tao, 2008, Zhang et al., 2009), as few as 6-10% of rural utilities in China appear to regularly disinfect water before piping it to users.

Due to the preference for boiled water, most households with large (19L) bottles also heat their water, using the electric heating device built into the water bottle stand (which even relatively poor households also own). The use of bottled water in China has grown substantially in recent years, and in those publications which report specific contaminants and concentrations, a significant proportion of samples often exceed national microbial contaminant standards (e.g., Li, 2004, Jia and Wang, 2009). For example, a recent government-led investigation found that 23.8% of the bottled water inspected did not meet China's standards, and 89% of those below-standards were large bottles (>15L), the kind used in many rural households (CFDA, 2014).

[2] My calculations based on the JMP's overall estimate that 112 million Chinese lack access to an "improved" water source (using the official population for 2012 and a 52.5:47.5 rural:urban ratio).

2. Methods

2.1 Study design, sampling, data collection, and data analyses

For details related to the study design, field sites and population; sample size calculation and random sampling of villages; household surveys, enumerator training, participant eligibility criteria, and random household selection; water sampling and analysis, as well as other information, see Chapter II.

2.2 Conceptual framework

A conceptual framework was used to guide model construction. Intermediate and confounding variables are of particular concern when trying to understand likely causal pathways (Petersen et al., 2006), and if not properly addressed one may inadvertently interpret indirect effects from models built to estimate direct effects (Westreich and Greenland, 2013). Conceptual hierarchies provide a useful way to organize the primary variables hypothesized to influence an outcome of interest (e.g., water quality) and to identify would-be intermediate and confounding variables. Such frameworks help one visualize how “distal determinants” (usually socioeconomic variables) which do not impact the outcome directly, may do so via “proximate determinants” or intermediary variables which directly impact the outcome of interests (Victora et al., 1994).

Figure 1 is not intended to identify and link all causal pathways related to HWT and microbial contamination, rather it outlines the hierarchical conceptual framework used to guide the step-wise model creation presented below. The variables at the top are distal, and those in the middle are proximate, to varying degrees, with the likely intermediate causal variable “storage” and likely confounder “water source” clearly identified. This figure is similar to Figure One in Genser et al. (2006), which is based on the work of Victora et al. (1997).

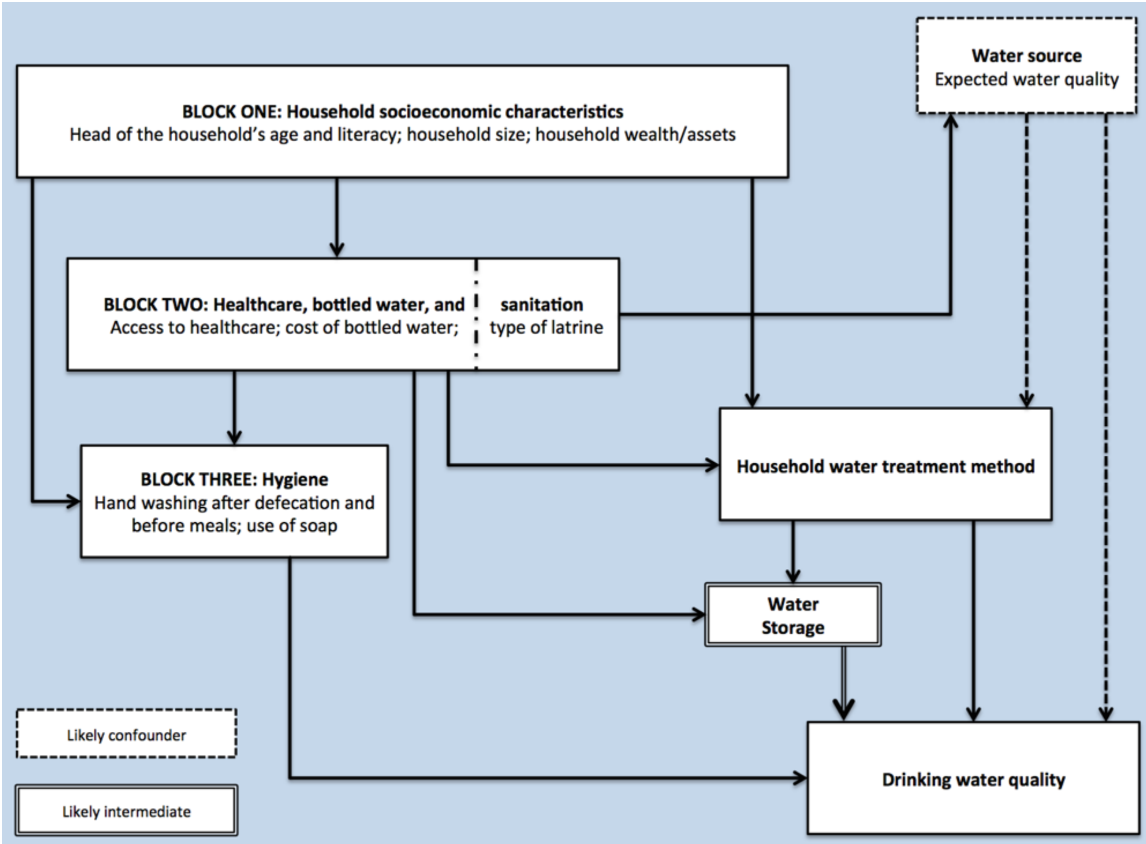

Figure 1: Simplified hierarchical conceptual framework of the primary factors which may impact microbial contamination of drinking water (used to guide model construction)

2.3 Data preparation, TTC transformation, and covariates

As described in the previous chapter, completed surveys were sent to Beijing where I trained staff to use a three-step process ("check-score-code", see: IFAD, 2014) for data quality-control and entry into Excel spreadsheets. After data entry, Luo Qing and I randomly selected two surveys from each village (6.6% of the entire sample) to manually check the accuracy of data entry. The data entry error rate was 0.15% (6 errors found in 30 surveys with 132 variables per survey).

As is usually the case, our TC and TTC data were positive skewed. Log_{10} transformation was used after assigning a value of one (rather than zero) to all cases where TC or TTC were below the detection limit (BDL). 38 coliform-related outlier cases were identified (8.5% of the total of 444 households with TC and TTC data available), appearing to be randomly distributed across the villages. All analyses were performed with and without outliers to ensure their removal did not significantly change the results. TC were detected in 93.7% of all households (93.1% with outliers removed) compared to 38.7% for TTC (40.6% with outliers removed); as such only the TTC data was used for the analyses below. See Appendix III for details on TC and TTC transformations and outlier identification as well as on variable creation and other details.

Covariates based on the conceptual framework in Figure 1 were created from survey questions. We designed our surveys to include multiple, overlapping, questions about and related to HWT, which helped us verify reported HWT use (see Table 1).

Table 1: Covariate data sources and definitions

Variable	Type	Survey item/s used (& checked against)	Definition/Notes
Treat drinking W	Dummy	74 (34, 84)	1=treat (boil or bottled), 0=untreated
Bl2BtUn	Categorical	74, 79 (21, 34, 81, 84, 89, 99)	1=boil elec. kettle, 2=boil open pot, 3=bottled, 4=untreated
-Boil w/elec. kettle -Boil w/open pot -Bottled Water	Dummy	74, 79 (21, 34, 81, 84, 89, 99)	Boil with elec. kettle = 1 0 0 Boil with open pot = 0 1 0 Bottled Water = 0 0 1 Untreated Water = 0 0 0
Improved W source	Dummy	32.3 (74)	1=improved, 0=unimproved (~JMP definitions)
Safe W storage	Dummy	88 (74)	1=safe storage, 0=unsafe
HH head is literate	Dummy	1	1=read newspaper without difficulty, 0=other
HH head's age	Continuous	Top of survey	
HH population	Continuous	2, 3, 4	Total pop. = adults in and out of the HH and children
No. TVs in HH (by HH pop.)	Continuous	71, 2, 3, 4	Mean number of TVs per HH pop. (mean of adults in and outside of HH plus all children in HH)
Min to health clinic	Continuous	11	
Mean bottled W price/village	Continuous	75, 76	Mean RMB per liter of bottled water by village (county means were used for villages 3, 9, and 10 to avoid too much missing data)
Improved latrine	Dummy	23 (24)	1=safe, 0=other
Wash hands post defecation	Dummy	30	1=always wash, 0=other
Soap likely used	Dummy	107	1=HH frequently uses soap, 0=does not (or no soap)
Wash hands before meals	Dummy	29	1=often or always wash, 0=other
HH = household			

2.4 Statistical analyses and multilevel mixed-effects modeling

Sampling weights were applied for population parameter estimation by using inverse proportions/probabilities to balance the 240 households sampled in County A and 210 in County B during the summer. For all analysis, missing data were ignored. Initial analysis consisted of t-tests, Wilcoxon rank-sum, ANOVA, and Bonferroni tests to examine TTC concentrations associated with different HWT methods and groupings. Bivariate analysis and graphing of TTC against relevant covariates was also conducted. See Appendix III for details.

Because households in our sample are nested in villages, the households cannot be considered as independent units of analysis (i.e., there is within-cluster dependence). Multilevel mixed-effects linear regression models (MLM) were therefore used to control for the impact of clustering, as well as possible confounders, intermediates, and other covariates. Between and within standard deviations (SD) were calculated for all covariates (see Appendix III).

In the model equations below, households are represented with *i*, and villages with *j* (i.e., level-1 units *i* are clustered in level-2 units *j*). MLM allows us to break down the errors into level-2 residuals, which capture the error for all units in a cluster and are denoted with ζ (zeta), and the level-1 residuals that are specific to the units in the clusters, and denoted with ϵ (epsilon). The between-cluster variance is represented using ψ (psi), which tells us, on average across our sample, what percentage of the variance is due to cluster membership. As with ordinary least squares (OLS) regression, the level-1 residuals provide an understanding of how the observations vary/deviate from the cluster means, and this within-cluster variance (i.e., the variance of *y* above and below the regression line for each cluster) is represented using ϑ theta). Thus, the total residual error is the sum of ζ and ϵ (since they are not correlated it is okay to sum them in this fashion); and similarly, the total residual variance, and the total variance of our dependent variable (DV) TTC, is the sum of ψ and ϑ (i.e., the variance components).

A consideration was whether to use Maximum Likelihood Estimation (MLE) or Restricted Maximum Likelihood Estimation (REML). Since we have a relatively small number of clusters (15) REML is likely a better and more conservative option (with 20+ clusters MLE is usually the preferred option) (Rabe-Hesketh and Skrondal, 2012). REML provides less biased variance components estimates generally, as compared to MLE, and this is especially the case when the data is balanced across clusters, such as ours.

Following the calculation of a null model (Equation 1), a series of models were calculated as discussed; the equation for the final model is presented in the Results section (Equation 2).

$$yLog_{10}TTC_{ij} = \beta_1 + \zeta_j + \epsilon_{ij}$$

Assuming: $\epsilon_{ij} \sim N(O, \theta)$, with ζ_j as the cluster-level error term, and $\zeta_j \sim N(O, \psi)$.

Equation 1: Null/unconditional variance components model

For all the models, likelihood ratio tests were used to test for the presence of a random intercept (to further justify the use of MLM versus OLS). The Coefficient of Determination (R^2) was calculated by taking the difference in total variance between each model and the Null model and dividing by the Null model's total variance (for more information see: Rabe-Hesketh and Skrondal, 2012: 136). Extensive sensitivity analysis, model diagnostics, and analysis of residuals were also performed. Modeling and other analysis were performed using STATA version 13.1 (Stata Corporation, College Station, TX).

3. Results

570 households were surveyed, but most of the data presented in this section are from the 450 households surveyed during the 2013 summer (as discussed in the previous chapter, this was because the winter sample size ended up being too small with regard to power requirements). However, winter TC, TTC, data are discussed briefly at the end of this section (and the winter SUMS data are discussed in Chapter IV).

3.1 Descriptive statistics for model covariates

Demographic characteristics were very similar across the two counties and closely in-line with village-level government data for mean number of adults and children per household, percentage of male-headed households, and the mean age of the household head, indicating representative sampling (see Appendix III). The known wealth differences between the two counties were likewise reflected in the summary statistics – see Table 2.

Table 2: Descriptive statistics for demographic and other variables by county and total sample

	County A	County B	Total Sample*
Survey info			
HHs surveyed (village codes)	240 (1-8)	210 (9-15)	450 (1-15)
Survey duration in minutes: mean (SD)	42.6 (7.8)	38.7 (6.7)	40.7 (7.4)
Total population in sampled HHs (unadjusted)	1,202* (1,288)	1,195* (1,121)	2,397 (2,409)
Respondent gender: %male (n)	49% (116)	53% (111)	51% (227)
Respondent age: mean (95% CI)	51.27 (49.3-53.3)	51.8 (49.7-53.9)	51.53 (49.4-53.7)
Demographics			
Head of HH gender: %male (n)	72% (171)	96% (202)	84% (373)
Head of HH age: mean (95% CI)	51.03 (49.4-52.7)	53.95 (52.4-55.6)	52.49 (50.9-53.9)
Adults >15y in HH: mean (95% CI)	3.55 (3.4-3.7)	3.59 (3.4-3.8)	3.57 (3.3-3.8)
Children <15y in HH: mean (95% CI)	1.08 (0.94-1.2)	1.06 (0.89-1.2)	1.07 (0.97-1.2)
HH population: mean (95% CI)	4.63 (4.4-4.9)	4.65 (4.4-4.9)	4.64 (4.3-5)
Mean annual income RMB (SD) [govt. data]	4,425 (769)	6,911 (994)	5,668 (SE=249)
Mean annual income USD (SD) [govt. data]	702 (122)	1,097 (158)	899 (SE=39.5)
SES related & other			
Head of HH fully literate: %(n)	49% (117)	85.5% (178)	67.5% (295)
Housing unit's roof is cement or concrete: %(n)	97.5% (234)	99.1% (208)	98.3% (442)
Number of TVs in HH (by HH pop.): mean (95% CI)	0.297 (0.27-0.32)	0.391 (0.36-0.42)	0.344 (0.32-0.37)
Minutes to nearest health clinic: mean (95% CI)	15.5 (13.8-17.1)	6.51 (6-7.1)	11.03 (8-14.1)
*Means, standard errors and confidence intervals (CI) adjusted with sample weights			

Prevalence estimates for the population are that 47.5% (95% CI=37.7-57.2) of households regularly boil their water (any method), 34.4% (95% CI=22.2-46.5) drink bottled water (with more than half usually heating the bottled water via a heating-unit inside the bottle stand), and the remaining 18.2% (95% CI=11.3-25.0) do not treat their drinking water.

To calculate the actual boiling ICC, I created a new variable based on the observation that many (if not most) of the ~35% of households who drink bottled water usually heat or boil the bottled water before drinking it. Based on other survey questions, I estimated that at least 72 of the 157 households drinking bottled water also heated/boiled that water, meaning ~63% of households in our sample regularly boil their drinking water. Using this variable, the actual ICC was 0.059, meaning our sample size was large enough to detect an effect size of ~±7%, rather than the planned-for effect size of ±5%. Ignoring the impact of clustering, our study was powered at the 0.8 level (alpha=0.043) to detect a ±6% difference in boiling proportion (see Appendix III for details).

Disaggregating the 47.5% of boilers, I estimated that 20.3% (95% CI=11.5-29.1) of households boil with pots and 27.1% (95% CI=17.2-37.0) boil with electric kettles (with <5% of this group using small kettles or pots placed on stand-alone electric burners). 99.8% of all households use electricity for lighting, suggesting universal access.

While less than half of all households have water piped from a small-scale utility, nearly all households (97.6%) reported having a piped source of water in their home or courtyard (from utilities, rainwater harvesting cisterns, wells, boreholes, etc.). Reported two-week diarrhea incidence was relatively low at 3.8% of all households - see Table 3 for additional information.

Table 3: Descriptive statistics for HWT and WASH variables

	County A	County B	Total Sample*
Binary HWT methods			
HHs that treat DW (boil or bottled): % (n)	91.6% (218)	73.7% (154)	82.6% (372)
HHs that boil non-bottled DW: % (n)	55% (131)	40% (84)	47.6% (215)
All HHs that boil DW (includes 72 bottled W HHs): % (n)	72.9% (175)	53.3% (112)	63.1% (287)
Four Primary HWT Methods			
HHs that boil with elec. kettles: % (n)	27% (65)	27% (57)	27.3% (122)
HHs that boil with open pots: % (n)	28% (66)	13% (27)	20.3% (93)
HHs that drink bottled water: % (n)	36.5% (87)	33.5% (70)	35% (157)
HHs that drink untreated water: % (n)	8% (19)	26% (55)	17.4% (75)
Water related			
HHs with water tap in/near home (any source): % (n)	96.6% (227)	98.6% (207)	97.6% (434)
HHs who report adults always drink treated water: % (n)	69.3% (165)	42.5% (88)	56% (253)
Respondent reported diarrhea in last two weeks: % (n)	4.6% (11)	2.9% (6)	3.8% (17)
Sanitation			
HHs with improved latrine: % (n)	87.5% (209)	83.4% (176)	85.6% (385)
HHs with private enclosed pour-flush toilet: % (n)	63.2% (151)	73.8% (155)	68.5% (306)
HHs with private flush toilet: % (n)	12.6% (30)	9.5% (20)	11% (50)
Hand washing			
Reported hand washing before meals: % (n)	82.5% (198)	86.2% (181)	84.4% (379)
Reported hand washing after defecation: % (n)	45% (108)	66.7% (140)	55.8% (248)
Reported use of soap: % (n)	65.6% (118)	25% (50)	42.9% (168)
Soap observed by enumerator & likely used: % (n)	55.3% (131)	27.6% (58)	41.4% (189)
***Proportions adjusted with sample weights | 38 outliers removed**			

The congruity between the 42.9% of households who reported using soap and 41.4% of households where enumerators observed soap that appeared to be used regularly is particularly noteworthy: see Figure 2 for proportions in each village. These findings contrast starkly with those from a WASH study on courtesy bias where 97% reported soap use but it was observed for only 68% (Manun'Ebo et al., 1997). This suggests responses to other questions that could evoke a social desirability bias are likely also relatively well-aligned with actual practice/behavior.

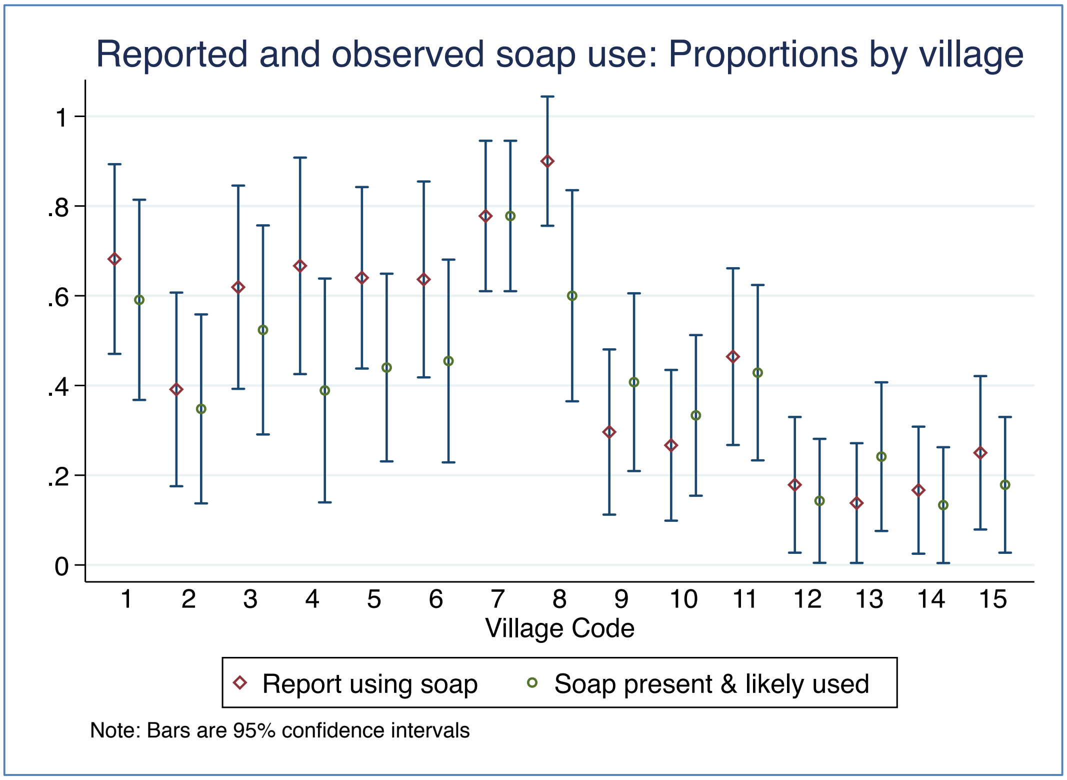

Figure 2: Reported and observed soap use: Proportions by village

3.2 HWT methods and water quality data

Among the HWT methods, TTC counts and concentrations were the lowest for households boiling with electric kettles: TTC was detected in only 28.4% of such households, and geometric mean TTC were 73% lower than households with untreated water - see Table 4 where arithmetic and geometric means are presented for added clarity (WHO, 2004). Raw Log_{10} TTC data and mean concentrations by HWT method are presented in Figure 3 (see Appendix III for more details).

Table 4: Summary statistics for Thermotolerant Coliforms concentrations by HWT method

HWT method	HHs in each HWT group: %(n)	TTC detected in each HWT group: %(n)	Arithmetic Mean TTC (MPN/100mL)		Geometric Mean TTC (MPN/100mL)	
			Mean	% lower than untreated (diff.)	Mean	% lower than untreated (diff.)
Boil w/elec. kettle	26.9% (109)	28.4% (31)	14.93	72% (39.2)	2.33	73% (6.2)
Boil w/open pot	20.7% (84)	42.9% (36)	25.27	53% (28.9)	3.86	55% (4.7)
Bottled water	34.2% (139)	40.3% (56)	27.72	49% (26.4)	3.31	61% (5.2)
Untreated water	17.5% (71)	57.8% (41)	54.14	0% (n/a)	8.52	0% (n/a)
Note: Data exclude 38 outlier HHs and proportions are not adjusted with sampling weights						

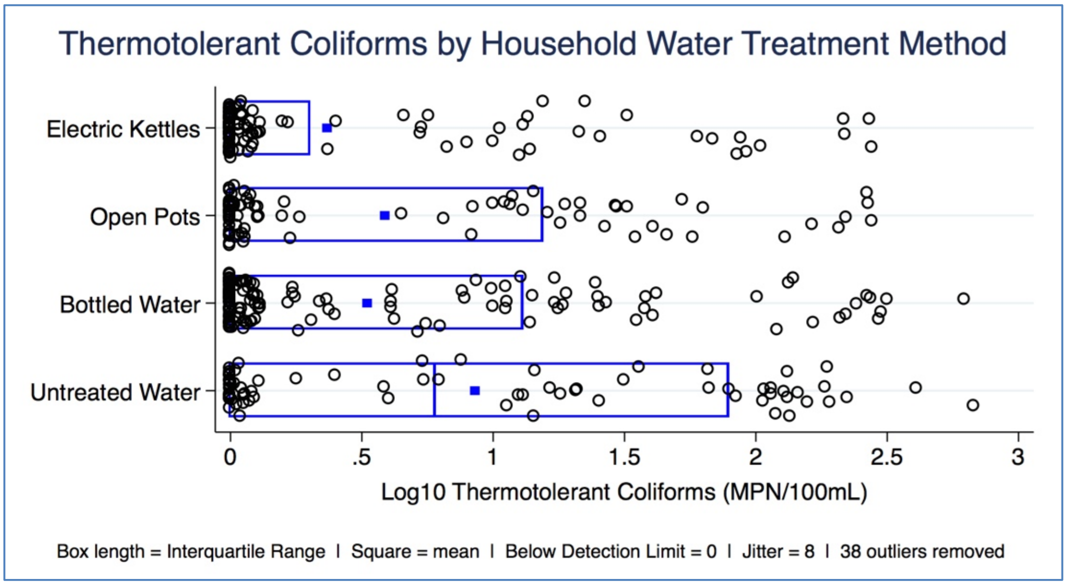

Figure 3: Log_{10} TTC concentrations by HWT method

With regard to the physicochemical parameters measured during the summer, across the 15 villages the mean pH was 7.78 (SD=0.196), turbidity was <1 for all villages, mean total hardness was 177.6 mg/L (SD=48.57), mean fluoride was 0.2 mg/L (SD=0), mean nitrate was 1.95 mg/L (SD=1.87), mean chloride was 9.27 mg/L (SD=5.36), mean iron was 0.167 mg/L (SD=0.13), and the mean sulfate concentration was 10.18 (SD=15.59). Only sulfate concentrations were above the CCDC standards for villages 12 and 13. For the physicochemical parameters measured during the winter, no concentration was above the CCDC standards for any of the four villages, and my measurements were very similar with those of the CCDC, except for sulfate concentrations in village 6 (30mg/L versus the CCDC's 7.3 mg/L).

3.3 Model results

Table 5 summarizes the results for the initial modeling used to examine HWT methods, source quality, and safe storage in isolation. Model One established that, when analyzed in isolation, there is a half log reduction (p<0.001) in TTC concentrations for households that treat their water by any means (boiling or bottled) compared to households that do not treat their water. Model Two disaggregated this treatment binary into three HWT methods, all of which are clinically and statistically significant, with the strongest effect observed for households who boil with electric kettles.[3]

[3] The weighted average (based on their respective number of observations) of the three coefficients from Model Two yields a coefficient of -.465, which is very close to the coefficient of -.481 from Model One.

After analyzing potential confounder and intermediary variables in isolation (Models Three and Four), together (Model Six), and after controlling for HWT (Models Five and Seven [see Table 6]), I observed no significant influence on the three HWT coefficients or the Log_{10} TTC reductions associated with these variables.

Table 5: Model results: Log_{10} TTC coefficients for the Null Model through Model 6

	Model Number						
	Null	**1**	**2**	**3**	**4**	**5**	**6**
Fixed Part							
Treat drinking W (vs. no)		-0.48(0.11) ***					
Boil w/elec. kettle (vs. no)			-0.57(0.12) ***			-0.58(0.13) ***	
Boil w/open pot (vs. no)			-0.38(0.13) **			-0.36(0.14) **	
Drink bottled W (vs. no)			-0.45(0.12) ***			-0.42(0.12) **	
Improved W source (vs. no)				-0.08(0.09)			-0.08(0.09)
Safe W storage (vs. no)					-0.08(0.12)	-0.09(0.12)	-0.05(0.12)
Intercept	0.57(0.05) ***	0.96(0.10) ***	0.96(0.10) ***	0.60(0.07) ***	0.63(0.12) ***	1.01(0.15) ***	0.64(0.13) ***
Random Part							
Between-level $\sqrt{\psi}$	0.117	0.148	0.134	0.134	0.136	0.153	0.157
Within-level $\sqrt{\theta}$	0.800	0.779	0.779	0.796	0.795	0.774	0.791
Log-likelihood	-490.3	-478.4	-479.6	-486.7	-449.8	-439.9	-447.5
R^2	N/A	0.038	0.043	0.002	0.005	0.046	0.005
Coefficient (Standard Error) | * p<0.05; ** p<0.01; *** p<0.001							

After disaggregating the drinking water treatment (or untreated) binary into electric kettles, pots, and bottled water (Model Two), all three HWT methods were associated with significant Log_{10} TTC reductions, and the largest reduction, -0.57, p<0.001, was associated with electric kettles.

Following this initial analysis, covariates were added to the models in a step-wise fashion based on the block hierarchy in Figure 1 (see Table 6). Note that Models 8.2 and 9.2 are slightly revised versions of the original Models Eight and Nine. The equation for Model Ten, the final model, is presented below (Equation 2). Additional details and model outputs are in Appendix III.

$$yLog_{10}TTC_{ij} = \beta_1 + \beta_2 BoilElectricity_{ij} + \beta_3 BoilOtherFuels_{ij} + \beta_4 BottledW_{ij} + \beta_5 ImprovedSource_{ij} + \beta_6 SafeStorage_{ij} + \beta_7 HeadHHLiteracy_{ij} + \beta_8 HeadHHage_{ij} + + \beta_9 TVperCap_{ij} + \beta_{10} BottledWprice_{ij} + \beta_{11} HandwashPD_{ij} + \beta_{12} SoapUsed_{ij} + \beta_{13} HandwashBM_{ij} + \zeta_j + \epsilon_{ij}$$

Assuming: $\zeta_j | \boldsymbol{x}_{ij} \sim N(0, \psi)$, $\epsilon_{ij} | \zeta_j, \boldsymbol{x}_{ij} \sim N(O, \theta)$

Equation 2: Model Ten

The assumptions of zero mean and variance are conditional on the covariates in the model (which is why the **x** is in bold font).

The HWT coefficients and significant levels remained relatively constant across models. For Models Eight and Nine, if the head of the household was literate there was an associated 0.2 Log_{10} TTC reduction, which is the direction one would hypothesize (i.e., better-educated households would be more likely to effectively treat their drinking water). Aside from literacy, no other covariates were significant. Interestingly, there was a consistent and relatively strong effect (though not significant) for TV ownership, a proxy of household wealth, such that increased TV ownership was associated with less Log_{10} TTC contamination.

Generally, as a model's fit improves the variance (between and within) and log-likelihood will both decrease. That said, other variables not controlled for in these models inevitably contribute to the variation between villages (bias from improper water sampling and/or analysis may also contribute to this variation). While the R^2 is relatively small across models, it is not an indicator of goodness of fit, but rather of the linearity of the relationship between covariates and the DV. Model diagnostics and analysis of level-1 and level-2 residuals did not reveal any assumption violations or outliers (see Appendix III).

Thus, overall we see that after controlling for the influence of likely confounders and intermediaries (which are not associated with Log_{10} TTC), as well as the impact of clustering and other covariates we expect could impact the DV, HWT was consistently and significantly associated with Log_{10} TTC reductions as compared to households drinking untreated water. Across the models, boiling with electric kettles was consistently associated with the largest Log_{10} reductions (>0.55, p<0.001), and bottled water and boiling with open pots tended to have similar effect sizes for Log_{10} TTC reductions.

Table 6: Model results: Log_{10} TTC coefficients for Model 7 through Model 10

	Model Number					
	7	**8.1**	**8.2**	**9.1**	**9.2**	**10**
Block (from Fig. 1):		**1**		**1, 2**		**1, 2, 3**
Fixed Part						
Boil w/elec. kettle (vs. no)	-0.57(0.13) ***	-0.61(0.13) ***	-0.61(0.13) ***	-0.62(0.13) ***	-0.62(0.13) ***	-0.60(0.13) ***
Boil w/open pot (vs. no)	-0.37(0.14) **	-0.45(0.14) **	-0.45(0.14) **	-0.44(0.14) **	-0.46(0.14) **	-0.44(0.14) **
Drink bottled W (vs. no)	-0.43(0.12) ***	-0.44(0.12) ***	-0.44(0.12) ***	-0.45(0.13) ***	-0.46(0.13) ***	-0.45(0.13) ***
Improved W source (vs. no)	-0.07(0.09)	-0.04(0.09)	-0.04(0.09)	-0.05(0.10)	-0.05(0.10)	-0.04(0.10)
Safe W storage (vs. no)	-0.05(0.12)	-0.08(0.12)	-0.08(0.12)	-0.08(0.12)	-0.07(0.12)	-0.05(0.12)
HH head is literate (vs. no)		-0.21(0.09) *	-0.21(0.09) *	-0.20(0.10) *	-0.19(0.10) *	-0.17(0.10)
HH head's age (10 yrs)[a]		0.03(0.03)	0.03(0.03)	0.04(0.03)	0.03(0.03)	0.04(0.03)
HH population		-0.00(0.02)				
No. TVs in HH (by HH pop.)		-0.38(0.20)	-0.36(0.19)	-0.36(0.19)	-0.35(0.19)	-0.34(0.19)
Min to health clinic (10 min)[b]				-.03(0.05)		
Mean bottled W price/village[c]				0.58(0.70)	0.56(0.70)	0.72(0.72)
Improved latrine (vs. no)				-0.03(0.11)		
Wash post defecation (vs. no)						0.07(0.09)
Soap likely used (vs. no)						-0.06(0.09)
Wash before meals (vs. no)						-0.20(0.13)
Intercept	1.01(0.16) ***	1.15(0.27) ***	1.14(0.26) ***	0.91(0.39) *	0.91(0.39) *	0.92(0.40) *
Random Part						
Between-level $\sqrt{\psi}$	0.172	0.162	0.162	0.167	0.166	0.167
Within-level $\sqrt{\theta}$	0.771	0.758	0.757	0.760	0.757	0.758
Log-likelihood	-437.8	-432.4	-429.4	-426.5	-428.5	-428.1
R^2	0.045	0.083	0.083	0.081	0.081	0.081

Coefficient (Standard Error) | * p<0.05; ** p<0.01; *** p<0.001
a. Coefficient for a 10 year increase is shown, instead of a one year increase
b. Coefficient for a 10 minute increase in distance is shown, instead of a one minute increase
c. Large standard errors are because village means was used for each HH case/village

3.4 Sensitivity analyses

For the sensitivity analyses, Model 10 was also calculated: using OLS; using MLE; using MLE with sample weights at levels one, two, and both levels; with a more lenient covariate for soap (soap present but not necessarily used); with a stricter definition for safe water storage; with a more lenient definition for post defecation hand washing; without data collected by enumerators responsible for data entry errors; without the safe water storage and water source covariates (all combinations); without the hand washing covariates (all combinations); with three levels using "county" membership; with and without the 38 outlier cases; and lastly compared to the full model, with and without the HWT covariates. See Appendix III for summary tables.

In all of these models the effect size and significance of the three HWT covariates remained relatively constant. With the inclusion of the outlier cases the effect sizes for all three HWT covariates were stronger (and significant at $p<0.001$); thus, the effect sizes with the outliers removed provide conservative estimates. The full model without the HWT covariates further demonstrated that the HWT method appears to be the only variable consistently and significantly associated with Log_{10} TTC. Indeed, the Log_{10} TTC means for each HWT method derived from Model 10 were very similar to the unadjusted bivariate means.

3.5 Additional analyses

Overall, the primary drinking water source was not significantly associated with TTC concentrations. However, among households drinking untreated water, those with improved sources had mean Log_{10} TTC of 0.57 MPN/100mL (geometric mean = 3.74), which was significantly lower than the 1.17 MPN/100mL (geometric mean = 14.76) for households with unimproved sources (two-sided t-test with unequal variances, p=0.0057). This difference supports our overall findings, because one would expect that even moderately efficacious HWT would reduce TTC concentrations in contaminated source water, but if no HWT was used the source-water quality should largely dictate the drinking water quality.

Among households using electric kettles, shorter boiling durations were associated with significantly lower TTC concentrations. For households boiling 2-4 minutes geometric mean TTC = 1.72 MPN/100mL, for 5-9 minutes 2.18 MPN/100mL, for 10-14 minutes 2.52 MPN/100mL, and for boiling durations greater than 15 minutes, 6.52 MPN/100mL. I used a Kruskal Wallis test to confirm that these differences were significant, as was the trend such that as boiling duration increases so do TTC concentrations (p=0.0487); a score test for a trend of odds ratios was also significant (p=0.0026).

To analyze this association further, I used multilevel mixed-effects regression; after controlling for household size, I found that for each additional minute of boiling with electric kettles there was a 0.027 MPN/100mL increase in Log_{10} TTC (SE=0.012, p=0.03). When I controlled for all the covariates from Model Ten, the effect size and direction remained essentially the same (0.029 MPN/100mL, SE=0.014, p=0.036). However, when I conducted the same analysis for boiling durations among pot users, I found no such relationship (-0.001 MPN/100mL, SE=0.012, p=0.932). These time-related analyses are discussed in greater detail in the next chapter. With regard to bottled water users, I observed no relationship between bottled water price and water quality – see Chapter V for more detailed analyses related to bottled water.

Overall, compared to households using electric kettles, households that did not treat their water were twice as likely to have TTC detected (risk ratio=2.03, p<0.001) – see Table 7. 5.3% of respondents from households not treating their water reported one or more cases of diarrhea over the previous two weeks, compared to 4.6% of bottled water users, 3.3% of electric kettles users, and 2.2% open pot users; however, these differences in expected frequencies were not significant (Chi^2=1.49, p=0.69) – perhaps because this study was not powered to detect differences in health related outcomes such as diarrhea. Figure 4 provides an overview of risk exposure by HWT method (a comparison with and without outliers is in Appendix III).

Table 7: Risk ratios for TTC contamination by HWT method (with and without outliers)

	38 outliers removed		All data (includes outliers)	
	Risk Ratio (95% CI)	**p-value**	**Risk Ratio (95% CI)**	**p-value**
No treatment	1*	n/a	1*	n/a
Boil w/elec. kettle	2.03 (1.42-2.90)	0.0001	2.25 (1.59-3.19)	0.0000
Boil w/open pot	1.35 (0.98-1.85)	0.0647	1.45 (1.07-1.97)	0.0162
Bottled water	1.43 (1.08-1.90)	0.0164	1.65 (1.25-2.18)	0.0007
*Reference category for unadjusted risk ratios of TTC detected (=1) versus no TTC detected (=0)				

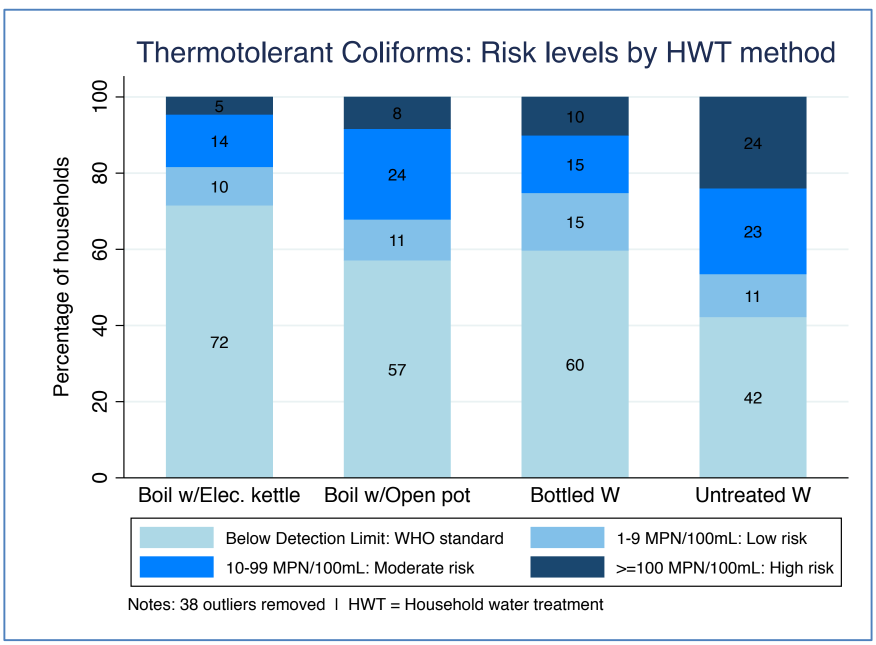

Figure 4: Thermotolerant Coliforms: Risk levels by HWT method

4. Discussion

4.1 Overview of the key findings as they relate to other HWT studies

This is the first China-based study I am are aware of to disaggregate HWT methods and evaluate their impact on microbial contamination in drinking water. This is also the first study I am aware of to identify the comparative effectiveness of boiling with electric kettles as compared to boiling with open pots (additional analyses with regard to this comparative advantage are discussed in the next chapter).

Among the HWT methods used in rural Guangxi, after using multilevel mixed-effects regression models to control for the impact of clustering, likely confounders, intermediates, and other relevant covariates, boiling with electric kettles was consistently associated with the highest Log_{10} TTC reductions as well as a 73% reduction in geometric mean TTC as compared to households drinking untreated water (risk ratio=2.03, p=0.0001).

These findings are inline with the 86%, 99%, and 97% reductions in post-boiling TTC concentrations (as compared to source water) found in Guatemala, India, and Vietnam respectively (Rosa et al., 2010, Clasen et al., 2008a, Clasen et al., 2008b), and the 98.5% reduction in *Escherichia coli* found in Cambodia (Brown and Sobsey, 2012). In Peru, where most HWT users boil their water, mean TTC in treated drinking water was 67% (urban) and 58% (rural) lower than source water (Rosa et al., 2014).

The covariates (e.g., safe water storage, latrine type) usually associated with microbiological water quality do not appear especially relevant in the context of rural Guangxi. I believe this is largely due to the cultural preference for boiled water, the near universal access to affordable electricity, excellent water access (and therefore little need for extended water storage), and relatively good sanitation and hygiene behaviors.

4.2 Comparing HWT rates and effectiveness with the 2013-2014 Winter data

As touched on above and discussed in the previous chapter, we were unable to revisit all 15 villages during the winter months to collect data from 450 households. Consequently, the limited winter data (n=120) is insufficiently powered for replicating the analyses presented here.

However, it is still worthwhile examining the overall TTC contamination by HWT method for the winter sample, limited as it is, since this is a key question and focal point of this research and due to our initial interest in understanding possible seasonal variation with regard to drinking water quality and rates of HWT use.

One hypothesized shift in HWT use patterns would be that some households who do not boil their water in the hot summer months may choose to boil during the cold winter months – as can be seen in Table 8, this may be the case for village nine.

Table 8: Summer and winter comparison if HWT rates in four villages

HWT Method	Village Code				
	3	6	9	10	Total
SUMMER					
Boil	93.33	32.14	66.67	51.72	61.54
Bottled	3.33	32.14	3.33	0.00	9.40
Untreated	3.33	35.71	30.00	48.28	29.06
WINTER					
Boil	74.07	50.00	96.67	73.33	73.50
Bottled	7.41	30.00	0.00	0.00	9.40
Untreated	18.52	20.00	3.33	26.67	17.09

More importantly, the relatively limited data from the winter sample do allow us to examine microbial water quality across different HWT methods. As can be seen in Figure 5, the lowest counts and concentrations of TTC are in the group using electric kettles, with the highest (as expected) in the group not treating their water. As with the summer data, TTC contamination levels for those using pots to boil or drinking bottled water fall in the middle of this range.

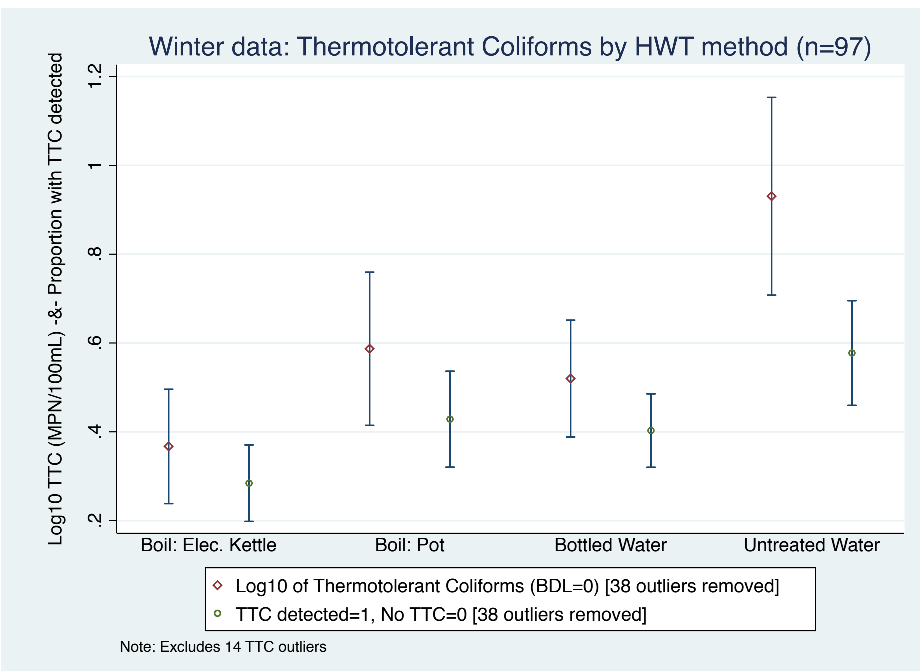

Figure 5: Winter data: TTC counts and concentrations by HWT method

4.3 Limitations to these analyses

As touched upon in the previous chapter, there are a number of limitations that ought to be taken into account when reviewing the results presented in this and the following two chapters.

With regard to random sampling, the use of three replacement villages in County A (instead of the randomly selected villages), though matched based on demographic and income data, may have created some selection bias.

Concerning observer bias, in some of the villages enumerators were required to "translate-as-you-go" since many respondents spoke only local dialects; this may have introduced comprehension difficulties. With regard to participant bias, while there are documented issues with the reliability of self-report data on HWT use (Rosa et al., 2014), I do not feel courtesy bias concerning HWT use was an issue of note. That said, of the households that reported using any kind of HWT, 25% reported that they "sometimes" or "often" drink untreated water, highlighting the issue of inconsistent HWT use (Enger et al., 2013, Clasen, 2015).

Lastly, in some cases it appears drinking water samples may have arrived to the county laboratories after the prescribed six hours, which may have resulted in higher TTC counts. This may also explain some of the 38 coliform outlier cases (though their distribution appeared random); though again, the exclusion of these outliers consistently resulted in more conservative estimates and effect sizes than when using the full dataset.

4.4 An initial look at the comparative advantages of electric kettles

What explains the significantly lower levels of TTC in drinking water samples from households that boil water with electric kettles as compared to households who boil with open pots?

For one, the electric kettles are automatic, so once turned on they heat the water until it boils and then automatically shut off. This means boiling water on demand is easy/convenient and the water reaches ~100C most of the time, as compared to open pots which are more labor intensive, and the water is not always brought to a boil. Though most microbes are inactivated at temperatures well below boiling (Spinks et al., 2006), electric kettles essentially guarantee the water is consistently brought close to the boiling point for full inactivation.

What is more, it is easier to boil smaller quantities of water with an electric kettle than a pot due to the convenience of pushing a button. Indeed, households using electric kettles report boiling significantly more than households boiling with pots (see analyses reported in the next chapter). This is relevant because it suggests that households using electric kettles boil more frequently, using smaller quantities of water, meaning there is less time for secondary contamination and microbial growth in standing water as compared to open pot users.

Secondary contamination is often suspected as the likely cause for microbial contamination in drinking water post treatment (Wright et al., 2004), and especially so for boiling (Luby et al., 2000, Psutka et al., 2011), since there is not residual disinfectant in the water. As reported above, the lowest levels of TTC overall were found in households using electric kettles and boiling for short durations.

Luby et al. (2000) also found that boiling durations of 1-5 minutes were associated with lower coliform counts than durations of 6-10+ minutes. Households reporting longer boiling durations may be boiling larger quantities of water (possibly due to larger household populations), which may in turn be left standing longer than smaller quantities (and thus be more susceptible to secondary contamination). It is also possibly that households boiling for longer durations use poorer quality, and thus less efficient and less effective, kettles.

Thus, one of the primary advantages of electric kettles is the limited opportunity for secondary (post-boiling) contamination because most electric kettles in rural China will not function unless the lid is closed. Since water can be poured out of the kettle without opening the lid it is likely that most households only open the lid when pouring in new water to boil, and thus there should be little opportunity for secondary contamination in cooled water, as compared to households using open pots. Similarly, since it is easier to boil-on-demand with an electric kettle there is less reason to store boiled water in other containers, as compared to open pot users.

Interestingly, only 63% (75/119) of households using electric kettles reported “never” or “rarely” drinking untreated water, compared to 75% (69/92) of open pot users, and 84% (132/157) of bottled water users. This inconsistent HWT use may explain some of the TTC contamination detected among HWT users (and may have dampened the effect sizes for electric kettle users).

5. Conclusions

Other studies have already documented the real-world effectiveness of boiling for microbiological reductions in drinking water (Luby et al., 2000, Clasen et al., 2008a, Clasen et al., 2008b, Rosa et al., 2010, Psutka et al., 2011, Sodha et al., 2011, Brown and Sobsey, 2012), but this is the first HWT study to suggest that, all things considered, there is a significant comparative advantage for boiling with electric kettles over boiling with open pots. This is also, as far as I am aware, the first English-language, peer-reviewed study of HWT and its microbiological effectiveness in China.

In rural China today, aside from a very small percentage of households who use filters, most households boil their water, a significant portion buy bottled water, and the rest drink untreated or (often untreated) piped water. However, an “improved” source is not necessarily a “safe” source, and of the study households whose primary drinking water source was piped water from a utility, only 26% thought the water quality was “good” or “very good”, with 67% considering it “satisfactory”. Of these same households, 58.5% boil their water and 34% buy bottled water.

Given the well-documented problems with HWT adoption (Waddington et al., 2009), rather than introducing new HWT technologies, the most practical way to expand access to microbiologically safe drinking water in rural China may be to build upon the existing preference for boiled water (and safety concerns around drinking water), and promote the expanded use of electric kettles. Such a strategy would have the added benefit of reducing HAP exposure. These implications of the findings described in this chapter are discussed in more detail in Chapter VI.

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Chapter IV

Electric Kettles, Pots, or Untreated?

Chapter IV: Table of Contents

1. Introduction

Now that we have an understanding of what HWT methods are used in rural Guangxi, and what the associated effectiveness is with regard to pathogen inactivation, we turn now to understanding which types of households use which HWT methods. In particular, these analyses are focused on understanding the predictors of boiling drinking water versus drinking untreated water, followed by an analyses of which variables predict the boiling with electric kettles versus boiling with pots. The goal of these analyses is to identify which demographic and socioeconomic variables are associated with potentially risk HWT behaviors such as drinking untreated water and HAP exposure from boiling with solid-fuels.

As far as I am aware, this is the first study (or at least the first published study) to focus on the predictors of HWT in rural China. As such, unfortunately there is no data with which to compare our results, so I they are contextualized here in the broader framework of drinking water supply and quality in rural China. Thanks in large part to historically unprecedented investments in rural water and sanitation infrastructure in China, diarrheal disease have dropped from the 10^{th} leading cause of premature death in 1990 to the 66^{th} in 2013 (IHME, 2016), corresponding to a 95.2% decrease in the age-standardized death rate associated with diarrheal disease (Zhou et al., 2015).

According to the best available national data, ~85% of rural Chinese households regularly combust wood, agricultural biomass, or coal to boil their drinking water (Tao, 2009). Based on our study data in Guangxi, ~48% of the study population regularly boil and if we include bottled water users who also heat or boil their water the estimate is ~63% (see Chapter III). Exposure to HAP, like cigarette smoke exposure, causes a number of cardiovascular and pulmonary cancers and other diseases (Chafe et al., 2014, Zhang and Smith, 2007, Smith et al., 2000, Zhang and Smith, 2003). In recent years, HAP was identified as one of the primary environmental causes of premature death globally, with 3.9 million attributable deaths in 2010 (Smith et al., 2014). HAP and black carbon emissions also exacerbate climate change (Bonjour et al., 2013, Ramanathan and Carmichael, 2008). In addition, when it cools, water boiled in open pots is susceptible to secondary microbial contamination (Wright et al., 2004).

At a national scale, boiling water with open pots heated over solid-fuels contributes directly to HAP in rural China and, in turn, to China's total air pollution burden and GHG emissions. Air pollution, is now the third leading risk factor for the current (2013) burden of disease in China (IHME, 2016). Previous research has shown that the combustion of solid-fuels at the household-level is responsible for the vast majority of black carbon emissions in China, as well as India (Chafe et al., 2014). Not only is this residential sector the largest overall source of PM2.5 in China, but "eighty percent of the PM2.5 emissions in this sector come from the combustion of biofuel (firewood and stalks) in rural households" (Lei et al., 2011: 945).

As discussed in the previous chapter, in spite of its popularity, it is not clear when the preference for boiled water took root in China. What is more, for many rural Chinese the boiling of drinking water is not considered a form of “treatment”. As such, were one to ask if a household treats their drinking water they might respond “no”, though if then asked if they regularly boil their drinking water they would respond “yes”.

On the supply side, aside from water-scarce regions in the north, the vast majority of China’s rural population has reliable access to drinking water. Indeed, by 2002, thanks to years of intensive investment into rural areas, 868 million rural Chinese had benefited from water supply infrastructure improvements (~92% of the entire rural population at that time) (陶勇, 2005). As cited in the previous chapter, according to the best publically available estimates, as many as 300 million or more rural Chinese lack access to safe drinking water, and microbial contamination is one of the primary culprits (李代鑫，杨广欣, 2006, Tao, 2008).

The struggle to provide universal access to safe drinking water in rural China remains an uphill battle, and it is in the more remote and poor regions of rural China where the greatest need remains. For example, of the rural water utilities constructed with support from the World Bank supported “Rural Water Supply and Sanitation Project in Guangxi” (1992-1998), a few years after project completion (2001) it was found that only ~5% were consistently meeting all management, quality, and cost-recovery standards, many were struggling to maintain basic water supply, and ~7% were no longer in operation (杨积军, 2002) .

Looking to the general WASH literature more broadly, there remains a need to better understand the predictors of HWT generally. As Brown and Sobsey (2012: 397) recently noted: “More research is needed to characterize how households make the decision to treat water and what conditions or circumstances prevent or promote more consistent use over time”.

2. Methods

For information on study design, field sites, sample size, sampling, water quality data, etc., see Chapters II and III.

2.1 Overview of covariate selection and use of MPAT-indicator values

To determine which variables appear to predict the use of different HWT methods, dependent variables (DV) were constructed as binary variables (Table 1), and a form of logistic regression was used to predict the probabilities associated with the DVs and a variety of independent variables (IV).

Due to the relatively large number of potential covariates, rather than conducting Chi Square tests to screen for significant bivariate associations between the DVs and potentially associated covariates, the choice of most demographics and socioeconomic indicator covariates was determined *a priori*, with an additional set of covariates identified using stepwise regression. If Chi Square tests were conducted for each DV and all possible covariates (from the household surveys), one would expect that a number of variables would be identified as significant (e.g., p-values <0.10 or <0.05) solely due to chance given the large pool of potential IVs. In addition, a few behavioral variables were used based on relevant research which suggests their potential power as predictive variables (described below).

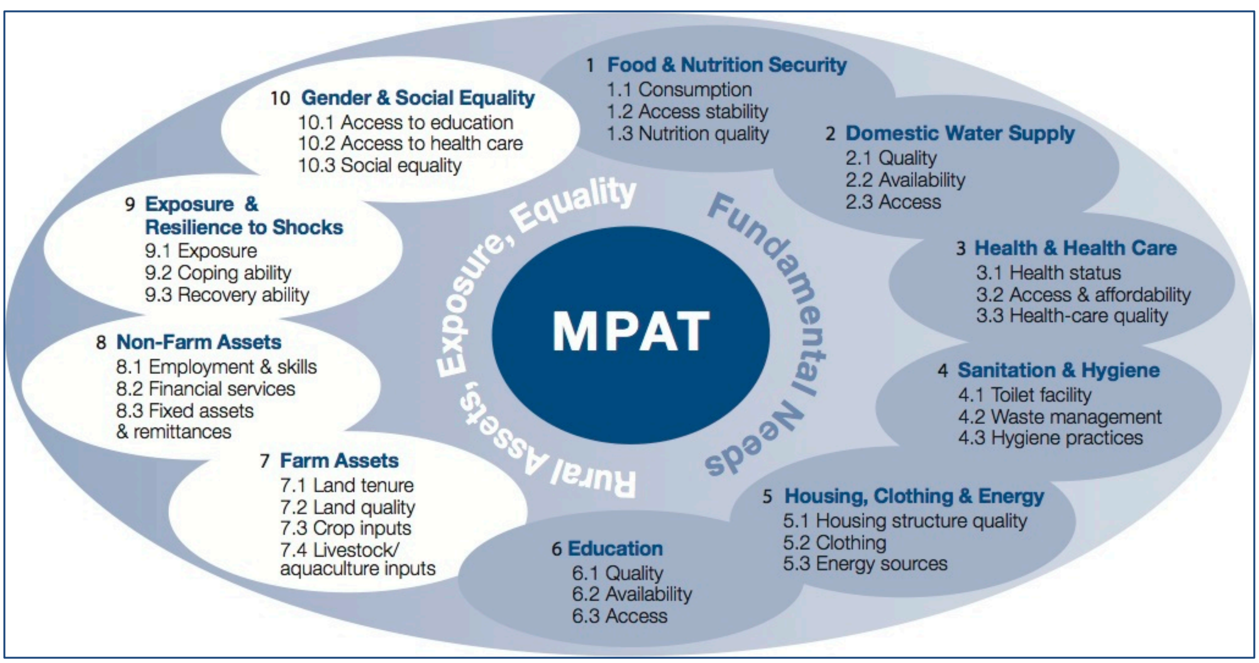

Figure 1: Overview of MPAT's components and subcomponents (www.ifad.org/mpat)

However, because this was the first known HWT-focused research study in China, it was understood that there was a good deal of uncertainty with regard to which other variables (if any) might be useful predictors of the preference for various HWT methods. As discussed earlier, I was unable to find any existing research on the drivers/predictors of HWT in rural China and, as a results, we cast a wide net with our initial data collection by using The Multidimensional Poverty Assessment Tool (MPAT, www.ifad.org/mpat) household survey.[1] Because MPAT converts an array of survey question responses to a 10-100 scale across components and subcomponents (100 being the best/high/positive score) it was a useful tool for this type of exploratory research – see Figure 1. Thus, I conducted an exploratory analysis (stepwise regression) using the MPAT component and subcomponent values in order to “dig” into the MPAT results from top-to-bottom to identify potentially relevant survey items from which additional covariates could be created, provided of course there was a sufficiently feasible causal link with the outcomes.

It is beyond the scope of this chapter to introduce and describe MPAT; interested readers may consult www.ifad.org/mpat and my past work (IFAD, 2014, Cohen, 2009, Cohen, 2010, Cohen and Saisana, 2014).

2.2 Dependent variable creation

HWT methods were classified and crosschecked against relevant survey items (as discussed in Chapter III). Three binary dummies were created to serve as dependent variables (DV), or outcomes variables, for the modeling described below (Table 1).

Table 1: Binary/dummy outcome variables (aka, Dependent Variables)

DV: Variable name	Dummy coding			Observations per model		
	1 vs 0	1	0	Max possible	Ignored	Missing
BoilUn_D	Boil vs Untreated	215	75	290	157	3
KettlePot_D	Boil E. Kettle vs Boil Pot	122	93	215	232	3

[1] Due to censorship of some survey questions we were unable to calculate all the MPAT subcomponents and components fully – see the Methods Chapter for more information, and see Chapter II for a justification for using MPAT and an explanation of how the MPAT components are potentially link/relate to water generally.

2.3 Demographic, socioeconomic, and behavioral covariates

Income was theorized as a key predictor of a households HWT use. Unfortunately, as discussed earlier, we were unable to collect sufficient data to estimate likely income, and the reported income data was aggregated at the village level, providing little insight into within-village income variability. As such, a number of proxies were used in order to examine and control for indicators predicted to be associated with HWT, and indicators which could also serve as proxies of household income or wealth. In addition to the demographic and socioeconomic covariates usually controlled for (e.g., household size, head of the household's gender, proxies for income) behavioral variables were also controlled for, based in part on the conceptual framework shown in Figure 2.

Behavioral psychology research on HWT suggests that perceptions about family members' and neighbors' use of HWT can influence a household's decision to do the same (Mosler, 2012, Mosler et al., 2010, Mosler and Kraemer, 2011). As such, we asked respondents how many of their relatives and neighbors in the village/area likely boiled water (variable names: RelativesBoil_D and NeighborsBoil_D).

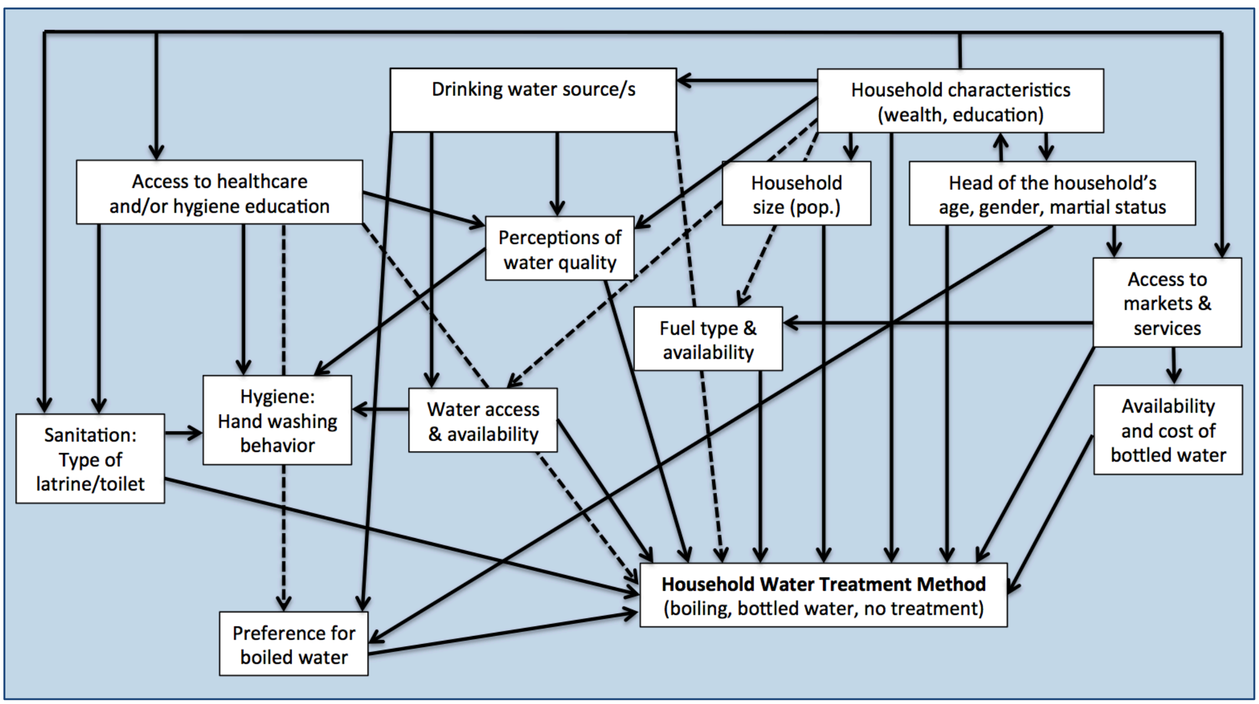

Figure 2: Conceptual framework of primary factors hypothesized to impact HWT use

Household survey question 93 (Q93) asked respondents what they believed would happen if a person drank untreated water; the responses were divided into "nothing will happen" and "something negative will happen" to create a variable to control for these beliefs (PercNoTreatOK_D). However, this question was, as expected, too predictive of the decision not to treat drinking water and thus while it provided a useful "reality check" with regard to the internal consistency of our data, it was not used in the modeling described below.

Q104 asked respondents in households that did not buy/drink bottled water why this was. All the responses and "other" responses were recoded into the dummy variables shown at the bottom of Table 2 (see Appendix IV for details). These data were used for some secondary analysis here, and additional analysis in the following chapter. Lastly, as discussed before, we lacked a reliable variable for household income or wealth, and thus used a number of proxies (Table 2).

2.4 Step-wise process for selecting MPAT-derived covariates

As discussed above, additional covariates were derived from the MPAT indicator results via a three-stage exploratory process (Figure 3) using forward and backward step-wise (single-level) logistic regression for the primary DV comparing Boiled/Untreated, as well as another DV comparing Bottled/Untreated (used for this purpose to identify potential additional covariates for the analyses comparing Bottled/Boil) (see Appendix IV for details and model outputs).

First, stepwise logistic regression was used with the MPAT component values[2] and a probability threshold of 0.2 (i.e., the minimum p-value for component inclusion in the final model). Backward stepwise logistic regression was also used with a probability threshold of 0.2 for removal from the model. MPAT components that had no association with the DVs in either the forward or backward stepwise regression models were not included in the next step of modeling.

In step two, stepwise logistic regression (forward and backward) was used with all the MPAT subcomponent results belonging to the MPAT components identified in the previous stage, but this time using a probability threshold of 0.15. This step was used to identify which MPAT subcomponents might contain survey questions significantly associated with the DVs.

Finally, the third step of the process was conducted to determine which specific survey items (survey questions) from the MPAT subcomponents identified in step two would remain in the models. For this third round, a probability threshold of 0.15 was used again (forward and backward stepwise logistic regression).

This exploratory process helped narrow in on survey questions that have a high probability of impacting HWT method choices in some fashion. The MPAT survey questions identified via these steps are described in Table 3.

[2] Subcomponent 6.3 was used in place of component six because there was no available data for subcomponents 6.1 and 6.2 (due to survey item censorship).

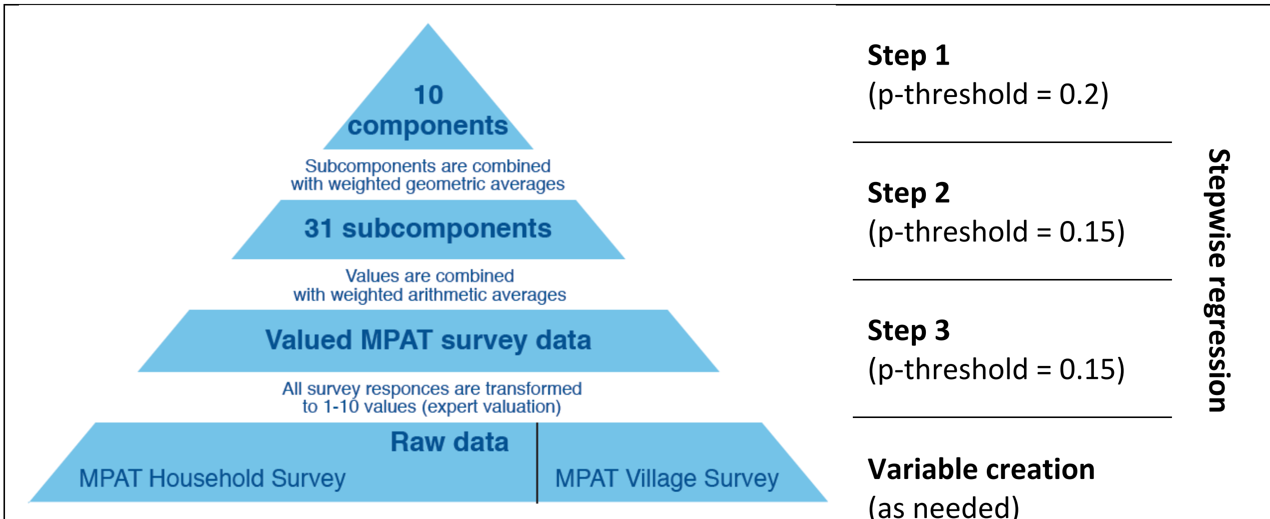

Figure reproduced from IFAD (2014: 159)

Figure 3: MPAT indicator aggregation scheme and associated stepwise regression thresholds

2.5 Statistical analyses and modeling

OR and RRs were calculated for covariates with ostensibly different proportions across HWT methods. For the primary analyses, I used a modified Poisson regression with cluster-robust standard errors (SE) in order to estimate risk ratios, rather than odds ratios. For all analysis, missing data were ignored.

With regard to model construction, as with the previous chapter, I used a hierarchical method to construct the models analyzing covariates one building block at a time – first in isolation and then incrementally as I built the models. However, whereas Victora et al (Victora et al., 1994, Victora et al., 1997) recommend starting with the distal hierarchical blocks and building toward the proximate blocks (as was done in the previous chapter), since here the focus is on binary predictors of risk, I decided to instead load the models with the variables theorized to be most proximate first, and then build out to include the most distal variables last. This was done also because the focus of the analysis here is on would-be behavioral drivers, and so it is more valuable to see how these would-be effects are potentially dampened/modified or explained by distal variables.

A number of researchers have pointed out that when an outcome is not rare in a population, odds ratios (OR) tend to be much larger than the risk ratios (RR), and when the outcome is relatively rare (e.g., <10% incidence) the OR and RR will be approximately equivalent (Altman et al., 1998, Thompson et al., 1998). In addition, some feel that policy makers and researchers are more readily able to interpret RR as compared to OR. Therefore, for analyses of relatively common outcomes, such as the HWT methods studied here, it is preferable to use RR.

With regard to model selection to estimate cluster-adjusted RRs for binary outcomes (e.g., boil=1, untreated=0), after reviewing the literature and a number of different modeling options, I chose to use a modified Poisson regression with cluster-robust standard error estimates in order to calculate covariate RR. When using a generalized linear model for Poisson regression with a log link for binary outcomes and cross-sectional data, the exponentiated coefficients are RR (rather than incidence-rate ratios) (Cummings, 2009, Greenland, 2004, Zou, 2004, McNutt et al., 2003).

Zou (2004) also points out that this use of a log link makes the resulting RR estimates more robust to omitted covariates, as compared to using logistic regression. In addition, this method avoids the difficulties of convergence often faced when attempting to use a binomial distribution – which was the case when I explored using such a model for this data (even after trying it with the "difficult" option in Stata) (Zou, 2004, Cummings, 2009). Benjamin-Chung et al (2015) used similar analyses for their recently published work on soil-transmitted helminthes in Bangladesh.

In order to account for the impact of clustering, I used a robust variance estimation accounting for clustering (using the "vce(cluster aa3)" option in Stata) so that the variance-covariance matrix estimation of SE factored in intragroup correlation (rather than assuming the observations are all independent). Of course this use of cluster-robust SE estimates does not change the coefficient and corresponding RR estimates (the SE being the square root of the estimated variance), but it does have the effect of providing more conservative SE estimates and thus tighter confidence intervals, as compared to not accounting for clustering (see the Sensitivity Analyses in Appendix IV, as well as functional form checks and other data related to the primary modeling/analyses).

Thus, the covariates in each were modeled against the DVs in isolation, after which the blocks were added into the models in a step-wise fashion to understand the variable influence on the RRs, standard errors, and p-values. Thirdly, the full model (with all blocks) was adjusted by removing covariates that did not appear to be contributing sufficiently (small effect sizes and/or large p-values) and that did not exhibit significant associations when analyzed in isolation or with other block combinations. However, variables know to have a clear link to the DVs were kept in the models as controls (e.g., household size) even if the associated p-values were relatively large (another justification for keeping some theoretically relevant but statistically non-relevant variables in the final models is that they are not substantially impacting the effect sizes of interest and thus, all things considered, one could argue it is preferable to keep them in the final model as I have done). Note that for model adjustments, in most cases likelihood-ratio tests could not be used due to difference in the number of observations available for the full and restricted models; as such, I used Wald tests instead (see Appendix IV for details). This step-wise block construction can be better understood by consulting the summary tables for each model (Table 6, Table 7, and Table 8). Model diagnostics and sensitivity analyses were also conducted.

3. Results

3.1 MPAT results: Overview and water-related indicators

Before confidently using the MPAT component and subcomponent values to identify variables associated with the outcomes of interest it is only prudent to inspect the entire MPAT dataset. One method for evaluating the overall reliability of the MPAT indicators is to examine the correlations between components. With regard to indicator construction generally, each component should represent and measure a different construct (and no data should be used for multiple components – i.e., no double-counting). Thus, no pair of MPAT components should be highly correlated since the data upon which each component is based, while related to data in other components, measures a specific construct. Figure 4 is a scatterplot matrix where each component's values are plotted against the others (due to missing data, subcomponent 6.3 was used in place of component six. As can be seen, there is no immediate evidence of significant correlations between any pair of components.

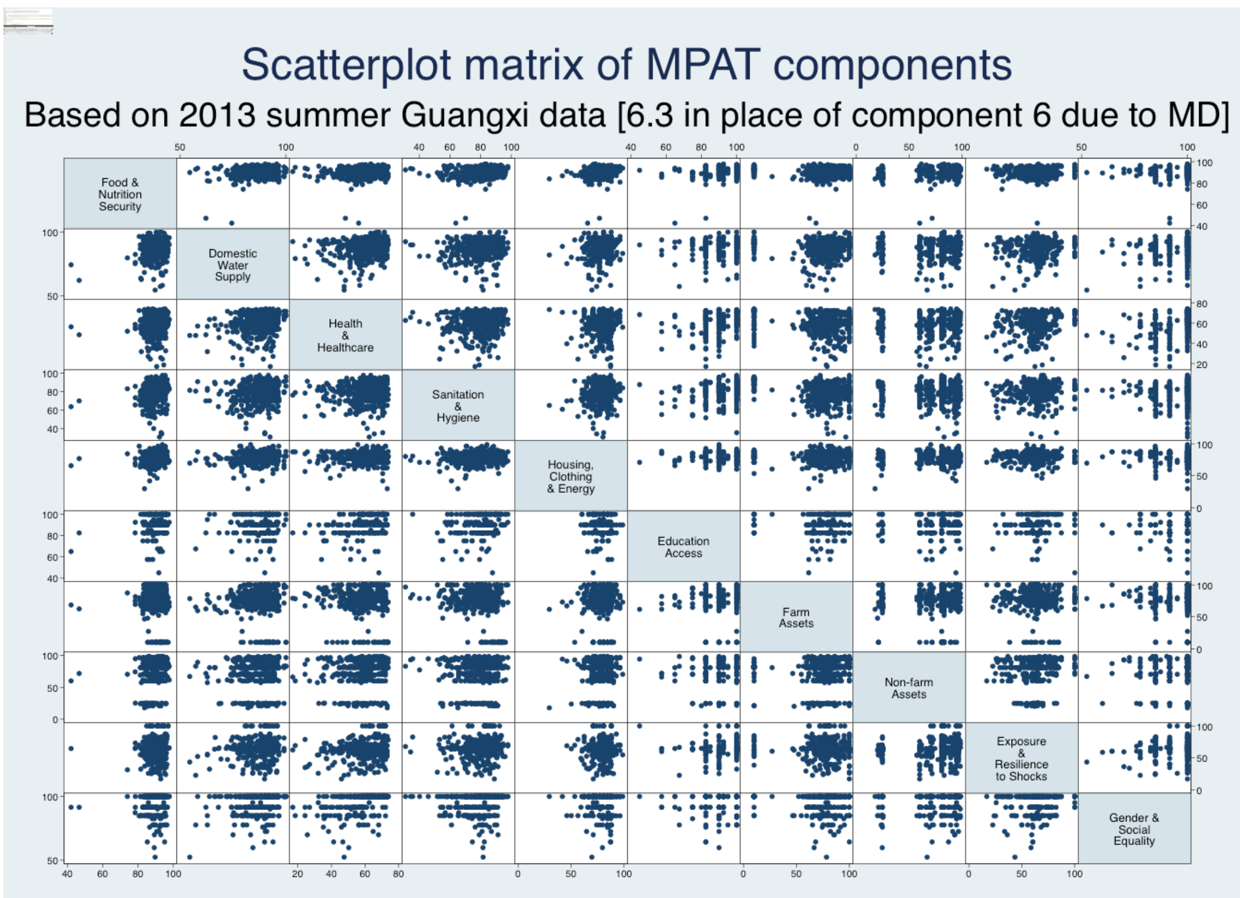

Figure 4: Scatterplot matrix of MPAT component values

The situation in rural China is, overall, much better than many low-income and middle-income countries where MPAT was designed to be used, as such it is not surprising that much of the data in the cells in Figure 4 is clustered to the right side of the indicator scales (i.e., closer to the maximum value of 100). While, overall, the situation as measured by MPAT is relatively good, the poorer status of County A and lower reported incomes in County A are reflected in the MPAT indicators, as can be see in the side-by-side comparison of MPAT components values in Figure 5 (see Appendix IV for more MPAT descriptive statistics).

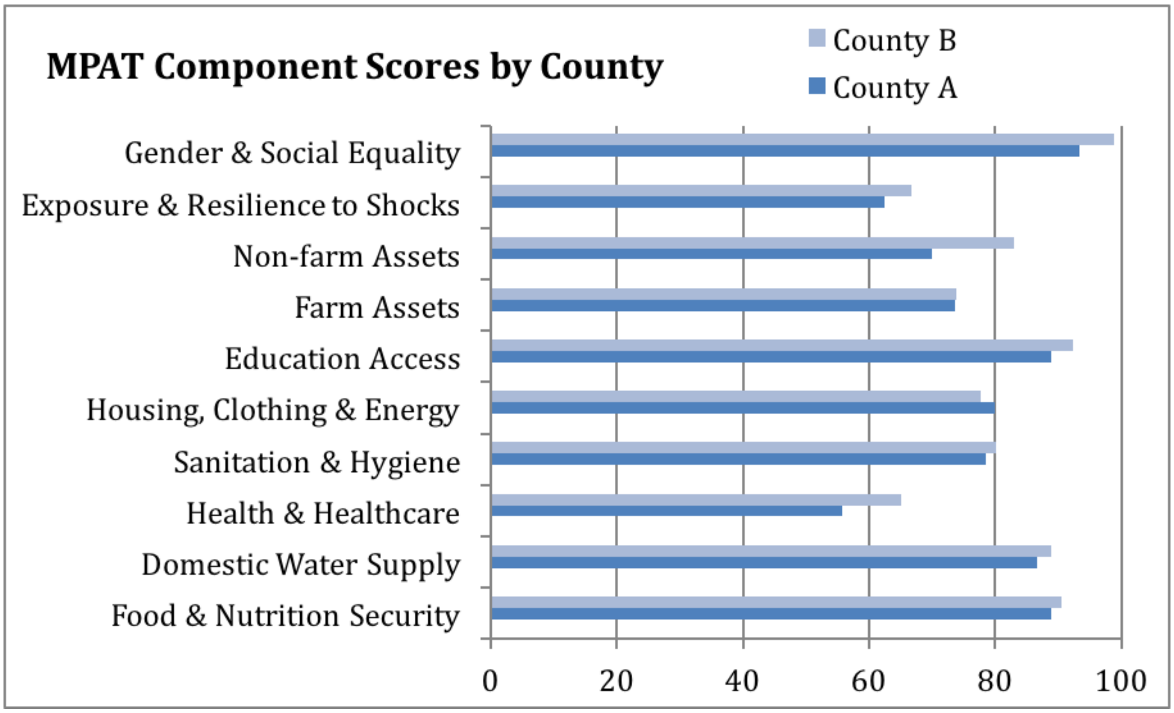

Figure 5: MPAT Components values by county

3.2 MPAT-derived covariates

Using the stepwise regression process outlined in the Methods section above, a number of variables derived from specific MPAT Household Survey questions were identified as significantly associated with the outcomes - see Table 2. The survey questions associated with the items identified are presented in Table 3) and a description of how new variables were created based on these questions can be found in Appendix IV. For Q17, 83% of HHs in County A have walls made of cement blocks which is assigned a value of 10 (the best value) under MPAT and 65% of HHs in County B have brick walls which is assigned a value of 8 under MPAT. Thus, when Q17 is converted into a binary, 98% of all households have structurally sound walls (i.e., the distinction between a score of 8 and 10 is lost since both fall under the value of one for the new dummy variable). As such, the other survey item from subcomponent 5.1 – the home's ability to withstand extreme weather (Q19) - was used to represent this construct (see Appendix IV for details). Q34 (whether the household treats their water or not) was not used for the modeling due to obvious collinearity issues with the outcomes.

Table 2: MPAT components, subcomponents, & survey items identified by stepwise regression

Step 1		**Step 2**		**Step 3**	
MPAT Components Identified (at p<0.2)		MPAT Subcomponents Identified (at p<0.15)		MPAT Survey Items Identified (at p<0.15)	
Boil/Un.	Bottled/Un.	Boil/Un.	Bottled/Un.	Boil/Un.	Bottled/Un.
2	2	2.1	2.1	34*	32 & 34*
3		3.2		13 & 14	11 & 14
5	5	5.1	5.1 & 5.3	21	17** & 21
6.3		---	---	---	---
8		---	---	---	---
10		10.2		---	---

*Q34 removed to avoid collinearity issues
**Replaced with Q19 (ability of home to withstand extreme weather)

Table 3: MPAT survey questions identified via stepwise logistic regression

Subcomponent Name (MPAT Component)	**Associated survey questions [and MPAT aggregation weights]**
2.1 Quality (Domestic water supply)	32) What is the **primary source** (meaning the source that water comes from immediately before being used) of the water your household uses for drinking and cooking inside the home? [45%] 34) Does your household treat water before drinking it (any treatment method: boiling, allowing to settle, filter, chemical treatment, etc.)? [35%]
3.2 Access & affordability (Health and health care)	11) How much time does it take for members of your household to reach the nearest health centre that can diagnose simple illness, or treat simple injuries and prescribe basic medicines? [25% or 38.5%] 13) How much time does it take for members of your household to reach the nearest health centre that can diagnose and treat complicated or serious illnesses or injuries (can perform surgery)? [35% or 0%] 14) Can your household afford professional treatment for serious illness or injury? [40% or 61.5%]
5.1 Housing structure quality (Housing, clothing & energy)	17) What is the **primary** construction material of the housing unit's exterior walls? [70%] 19) Can your home withstand strong winds, severe rain, snow or hail without significant damage [30%]
5.3 Energy sources (Housing, clothing & energy)	21) What is the **primary** fuel source your household uses for cooking? [40% or 57%]

3.3 Covariates summary and descriptive statistics by HWT method

Descriptions of all the variables used for the models are provided in Table 4, and summary statistics, disaggregated by HWT method, are provided in Table 5.

Table 4: Pre-selected and MPAT-derived covariates

Variable	Type	Survey item/s	Definition
Water & behavioral-related			
PercWQ_D	Dummy	38	1= HH perceives their drinking water quality to be good or very good, 0= other
ImprovedSource_D	Dummy	32	1= "Improved" water source, 0= Unimproved
RelativesBoil_D	Dummy	86	1= "most" or "all" of relatives boil, 0=other
NeighborsBoil_D	Dummy	87	1= "most" or "all" of relatives boil, 0=other
Access to health services			
BasicHealthAccess	Continuous	11	Minutes to reach nearest health clinic
AdvHealthAccess	Continuous	13	Minutes to reach nearest health center that can address serious illness or injury
AffordProfCare_D	Dummy	14	1= HH can afford professional medical care, 0= other
Economic indicators			
TVbyHH [per cap]	Continuous	71, pop. data	Number of TVs in HH/HH population
RMBvillageBottle_r19	~Continuous	74, 75, 76	Average cost of a 19L bottle of water per village
HomeDurability_D	Dummy	19	1= Home can withstand severe weather, 0= Home cannot withstand severe weather
SafeFuel_D	Dummy	21	1= HH uses safe fuel (no/low HAP potential), 0= other
Demographic & gender-related indicators			
head_hh_age	Continuous	Top of survey	Head of the HH's age
HHgender_D*	Dummy	Top of survey	1=Male, 0=Female or Joint (Female & Male)
Marital_D*	Dummy	Top of survey	1= head of HH is married, 0=other
Single_F** Single_M** Married_F** (Reference)	Dummy	Top of survey	1= Single F head of HH, 0= other 1= Single M head of HH, 0= other 1= Married F or F&M head of HH, 0= other All variables =0 (Married M head of HH)
Literacy_D	Dummy	1	1= head of the HH is literate, 0= illiterate
HHp_total_in	Continuous	2, 3, 4	Adults and children living in the HH
Miscellaneous: Reason HH does not buy bottled water [see Chapter V]			
Q104e Q104i Q104u Q104s (Reference)	Dummy	104, 87	1= Too expensive, 0= other 1= Inconvenient to get, 0= other 1= Unsafe, 0= other 1= Prefer spring water, 0= other (Other reasons) All variables = 0
Notes: HH = household | Variables derived from MPAT indicators in *italics* Variables marked with "**" are interaction terms that are used for some models instead variables marked "*"			

Table 5: Descriptive statistics for model variables by HWT method

	Boil: E. Kettle	Boil: Pot	Bottled	Untreated	Total (n)
Water & behavioral-related					
HH believes DWQ is good/very good: %	41.2	28.7	46.7	64.0	44.6 (190)
HH has improved drinking water source: %	55.7	55.1	39.7	39.2	47.6 (211)
HH believes most/all nearby relatives boil: %	55.3	75.8	44.2	6.5	50.1 (125)
HH believes most/all neighbors boil: %	54.6	75.4	45.3	9.1	50.8 (125)
Access to health services					
Minutes to clinic for basic care: Mean	12.4	15.6	9.1	8.8	11.3 (440)
Minutes to clinic for advanced care: Mean	28.0	30.9	22.7	23.8	26.0 (443)
HH can afford professional care: %	51.6	43.0	60.5	69.3	55.9 (250)
Economic indicators					
Number of TVs in HH / HH population: Mean	0.60	0.56	0.55	0.71	0.60 (440)
Village-average price for 19L W bottle: Mean	7.68	8.00	7.82	6.55	7.60 (447)
Home can withstand severe weather: %	93.2	86.1	81.9	88.9	87.0 (369)
HH uses safe fuel for cooking & heating: %	81.5	40.9	81.1	62.7	69.8 (300)
Demographic & gender-related indicators					
Head of the HH's age: Mean	52.0	56.7	49.8	53.1	52.4 (446)
Male-headed HHs: %	88.5	69.6	83.3	93.3	83.6 (372)
Married head of HH: %	95.0	83.3	90.1	94.4	90.7 (392)
Head of the HH is a single female: %	2.52	11.2	6.67	1.39	5.58 (24)
Head of the HH is a single male: %	2.52	5.62	3.33	4.17	3.72 (16)
Head of the HH is a married F or F&M: %	9.24	18.0	10.7	5.56	10.9 (47)
Head of the HH is a married male: %	85.7	65.2	79.3	88.9	79.8 (343)
Head of the HH is literate: %	66.7	46.2	74.7	76.0	66.8 (294)
HH population (live in HH >9 months): Mean	4.16	3.20	4.22	3.80	3.92 (447)

Notes: HH = household
Number of TVs in the HH is divided by the total population living in the HH 9> months/year
Total n excludes missing data (and totals are not adjusted with sample weights)

Looking at the apparent differences in proportions and means across HWT methods (Table 5) a few variables are of particular interest. Firstly, as a reality-check of sorts, we see that across HWT methods the highest proportion of households who believe their drinking water quality is good or very good are in the group that does not treat their water. Thus, if a household perceives their drinking water quality to be good or very good they are 27% less likely to boil their water (unadjusted RR=0.73, .62-.85, p<0.0001); put another way if a household perceives their drinking water quality to be good or very good, they are 2.3 times more likely to drink untreated water (unadjusted RR=2.3, 1.5-3.5, p<0.0001).

3.4 Cross-checking reported and observed drinking water quality

We can compare respondent's subjective perceptions of their drinking water quality with TTC concentrations and counts. As can be seen in Figure 6, across all villages (except village three) the MPAT subcomponent data from the MPAT "Domestic Water Supply" component indicates that access to water and the reliability of that access are both excellent – a finding that was also reflected in the data from the additional survey items added to the end of the household survey. However, the values for the water quality subcomponent were lower overall and more variable.

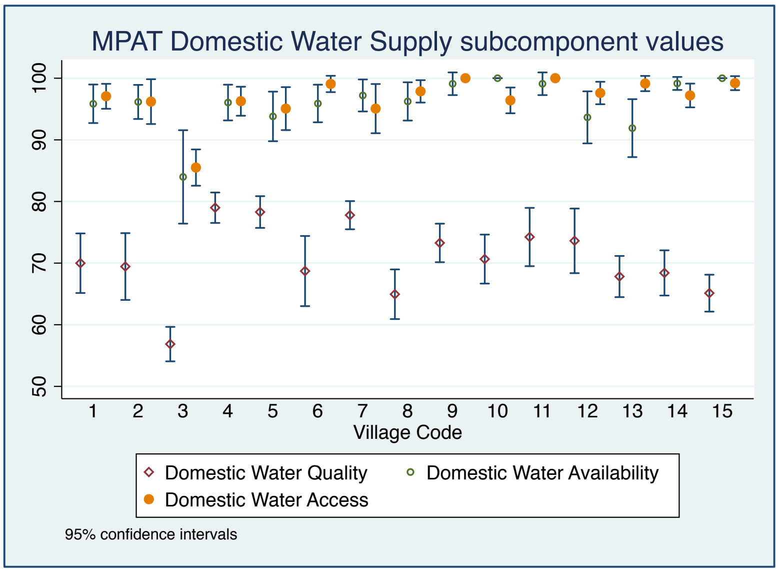

Figure 6: MPAT Domestic Water Supply subcomponent values by village

When we examine the association between the values for subcomponent 2.1, estimated "Domestic Water Quality", and our objective indicator of microbial water quality, TTC, we find that the difference between the mean MPAT 2.1 score for households with no TTC detected (71.8) is statistically significantly different than the mean MPAT 2.1 score for households with TTC detected (68.7) (two-sided t-test, p=0.0102). Using a non-parametric Wilcoxon rank-sum test we also find the difference in the rank distributions to be significant (p=0.0342). That said, this three-point difference in mean MPAT scores for subcomponent 2.1 is not necessarily clinically significant (i.e., the actual difference of only three points on a 10-100 scale, with a range of ~30-100 in our study, is not especially relevant).

Interestingly, when we examine one of the survey questions that contributes to MPAT subcomponent 2.1, Q38, "Generally, what do you think the quality of your household's drinking water is (before any treatment)?" and the associated TTC results, we find that both TTC concentrations (Figure 7) and TTC presence/absence (Figure 7) map reasonably well onto respondent's subjective perceptions of their water quality. Indeed, the lowest proportions and concentrations of TTC were found in samples from households who reported that their drinking water quality was “good” or “very good”. While the confidence intervals overlap, it appears that the overall trend of subjective perceptions may be roughly inline with the observed water quality results.

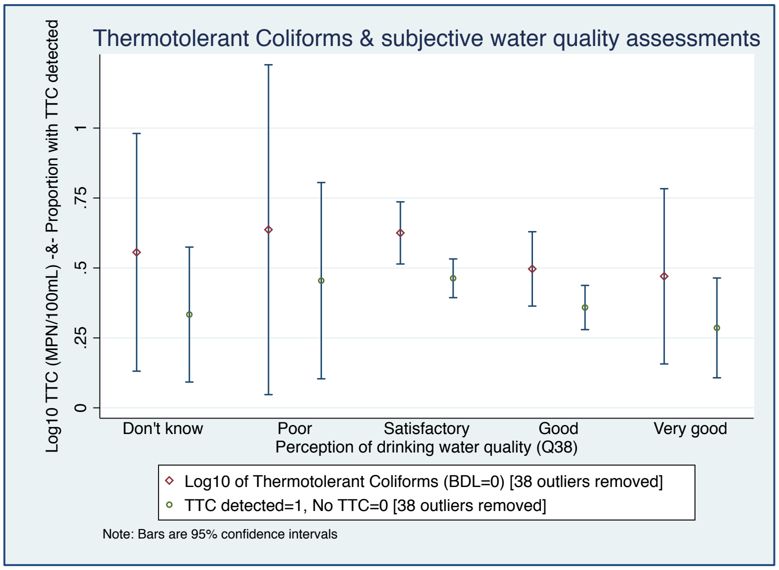

Figure 7: Thermotolerant Coliform concentrations & counts by household perceptions of water quality

3.4 Model results: Boil-vs-Untreated

Table 6: Boil-vs-Untreated Modified Poisson Regression Model results by covariate block & final model

	Risk Ratio (95% CI)			
				Final Model
Water & behavioral-related				
Believe DWQ is good/very good	0.75** (0.61-0.91)	0.78* (0.64-0.95)	0.79* (0.65-0.97)	0.78** (0.64-0.94)
Improved drinking water source	1.11 (0.91-1.34)	1.09 (0.92-1.29)	1.09 (0.93-1.27)	1.10 (0.93-1.29)
Access to health services				
Minutes to clinic for basic care		1.005** (1.002-1.008)	1.005** (1.002-1.009)	1.005** (1.002-1.008)
HH can afford professional care		0.90[a] (0.79-1.01)	0.91 (0.79-1.05)	0.91 (0.79-1.04)
Economic indicators				
TVs in HH / HH population			0.86 (0.70-1.05)	0.83[b] (0.68-1.02)
Home can withstand severe weather			1.12 (0.80-1.54)	1.12 (0.80-1.56)
Demographic & gender-related				
Head of the HH's age				1.003 (0.997-1.010)
HH head is married F or F&M				1.08 (0.87-1.35)
HH head is single male				0.95 (0.72-1.26)
HH head is single female				1.36** (1.12-1.66)
HH head is literate				1.05 (0.88-1.26)
HH population (live in HH >9 months)				0.997 (0.967-1.028)
Model indicators				
Log pseudo-likelihood	-259.2	-254.14	-237.51	-230.82
n	273	269	252	246
Notes: HH=household | * p<0.05; ** p<0.01; *** p<0.001 | [a] p=0.071 | [b] p=.076				

For model results by block by block in isolation, see Appendix IV. As can be seen in the final model (right column of Table 6), if a household believes their drinking water quality is good or very good, they are 22% less likely to boil their water (adjusted RR=0.78, 0.64-0.94, p<0.01); thus, the effect size of the adjusted risk (after controlling for the other variables in the model) is similar to that of the unadjusted risk (reported above), but somewhat smaller, which is as to be expected.

We can use the predicted mean probabilities from the model to graph each observation for a given covariate to visually examine the expected probability that a household will boil their water (probability=1) or will not treat their drinking water (probability=0). In Figure 8, we see that as the distance to the nearest health clinic which can provide basic health services increases (i.e., as access worsens), the probability that a household will boil their water increases. When we disaggregate based on the head of the household's gender, we see that for female or joint male-female headed households, the distance to the nearest health clinic does not appear to influence the decision to boil drinking water; however, for male-headed households the overall trend is similar to that observed for all households such that the further the clinic the higher the predicted probability that the household will boil their water.

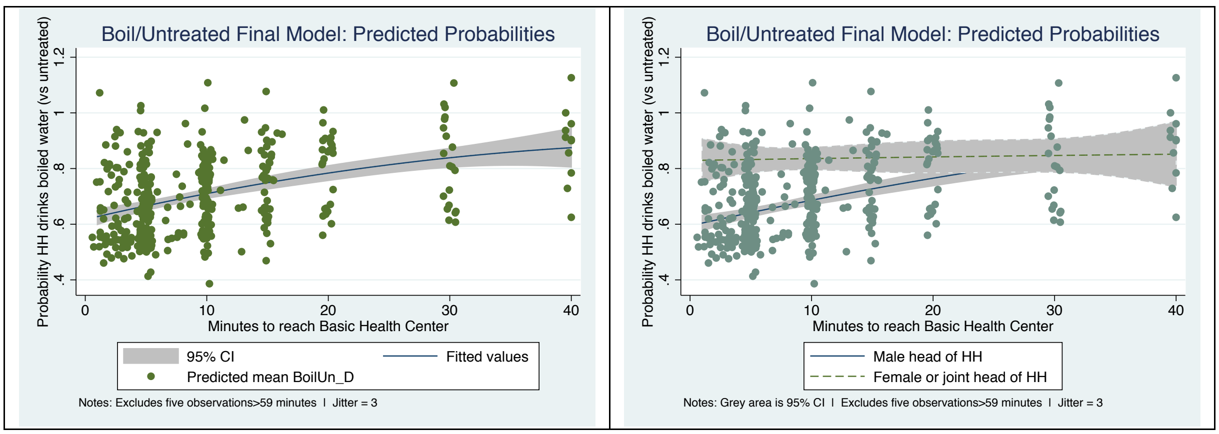

Figure 8: Predicted probabilities for boiling by time to health center and HH head's gender

In Figure 9, we see that as TV ownership rates increase the predicted likelihood of drinking untreated water increases. Households who believe their drinking water quality is good or very good are more likely to drink untreated water wherever they are on the TV ownership curve.

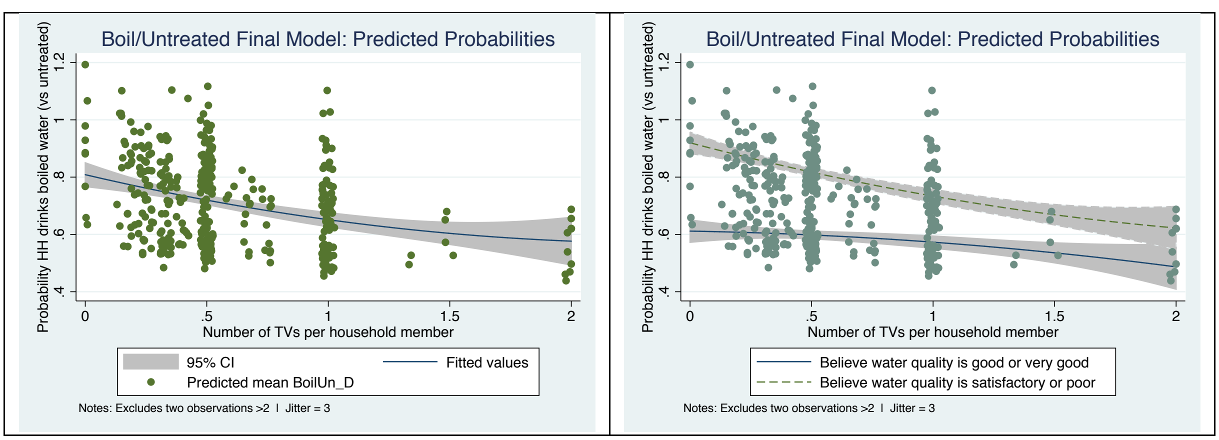

Figure 9: Predicted probabilities for boiling by TV ownership and perceptions of water quality

3.5 Model results: Kettle-vs-Pot

Table 7: Kettle-vs-Pot Modified Poisson Regression Model results by covariate block

	Risk Ratio (95% CI)			
Water & behavioral-related				
Believe DWQ is good/very good	1.23 (.81-1.88)	1.20 (.86-1.68)	1.22 (.87-1.70)	1.13 (.82-1.57)
Improved drinking water source	0.98 (0.58-1.65)	0.93 (0.58-1.50)	0.92 (0.56-1.50)	0.98 (0.63-1.52)
Access to health services				
Minutes to clinic for basic care		0.992 (0.967-1.017)	0.992 (0.964-1.020)	0.996 (0.972-1.021)
HH can afford professional care		0.96 (0.71-1.30)	0.91 (0.69-1.21)	0.94 (0.68-1.30)
Economic indicators				
TVs in HH / HH population			1.16 (0.90-1.50)	1.43** (1.20-1.75)
Home can withstand severe weather			1.25 (0.71-2.23)	1.07 (0.63-1.83)
Demographic & gender-related				
Head of the HH's age				0.990* (0.990-0.999)
HH head is male				1.14 (0.74-1.76)
HH head is married				1.42 (0.72-2.80)
HH head is literate				1.18 (0.82-1.69)
HH population (live in HH >9 months)				1.13*** (1.08-1.19)
Model indicators				
Log pseudo-likelihood	-176.89	-172.28	-160.55	-150.59
n	199	195	182	177
Notes: HH=household | * p<0.05; ** p<0.01; *** p<0.001				

For model results by block by block in isolation, see Appendix IV.

Table 8: Kettle-vs-Pot Modified Poisson Regression Model results

	Risk Ratio (95% CI)	
	Full Model	**Final Model**
Water & behavioral-related		
Believe DWQ is good/very good	1.13 (0.82-1.57)	1.12 (0.81-1.56)
Improved drinking water source	0.98 (0.63-1.52)	0.99 (0.64-1.54)
Access to health services		
Minutes to clinic for basic care	0.996 (0.972-1.021)	0.997 (0.974-1.021)
HH can afford professional care	0.94 (0.68-1.30)	---
Economic indicators		
TVs in HH / HH population	1.43** (1.20-1.75)	1.42** (1.16-1.74)
Home can withstand severe weather	1.07 (0.63-1.83)	1.04 (0.57-1.89)
Demographic & gender-related		
Head of the HH's age	0.990* (0.990-0.999)	0.989* (0.980-0.998)
HH head is male	1.14 (0.74-1.76)	1.14 (0.74-1.75)
HH head is married	1.42 (0.72-2.80)	1.43 (0.73-2.80)
HH head is literate	1.18 (0.82-1.69)	1.16 (0.83-1.63)
HH population (live in HH >9 months)	1.13*** (1.08-1.19)	1.13*** (1.07-1.19)
Model indicators		
Log pseudo-likelihood	-150.59	-150.63
n	177	177
Notes: HH=household | * p<0.05; ** p<0.01; *** p<0.001		

As with the previous model, we can use the predicted mean probabilities from the final model to graph each observation for a given covariate to visually examine the expected probability that a household will boil their water with an electric kettle (probability=1) or boil their water with a pot (probability=0) – see figures below.

In Figure 10, we see that as the household head's age increases the probability that the household will boil with a pot increases (i.e., households with older heads of household are more likely to boil with a pot rather than an electric kettle). If we stratify this linear estimate based on the head of the household's literacy, we see that, overall, literate household heads are more likely to use electric kettles, though the difference may not be significant at the upper and lower end of the age spectrum.

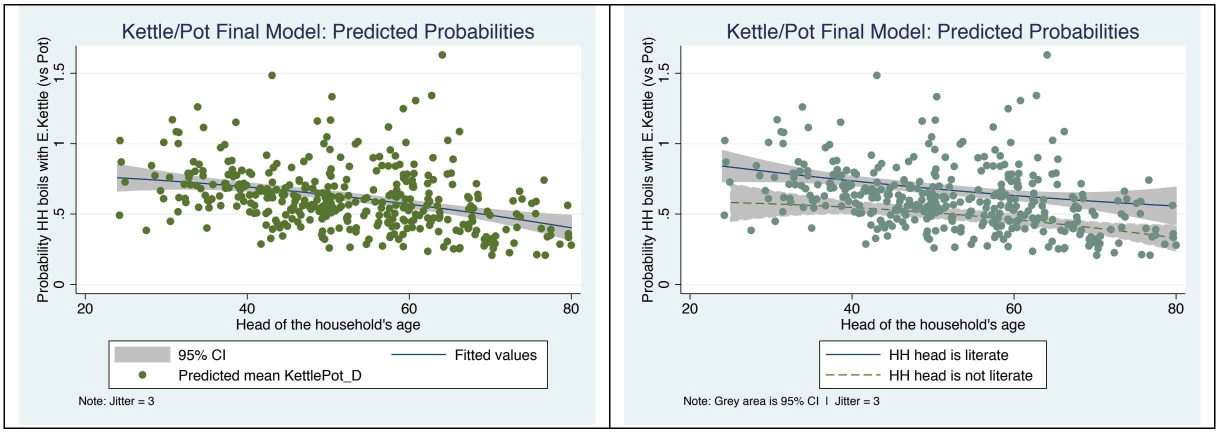

Figure 10: Predicted probabilities for using an electric kettle (vs a pot) by head of the household age and literacy

Similarly, in Figure 11 we see that male headed households are more likely to use electric kettles overall. Comparing this with the findings from the previous model, this suggests that female headed households are more likely to boil than to drink untreated water, but that boiling is more likely done with a pot than an electric kettle.

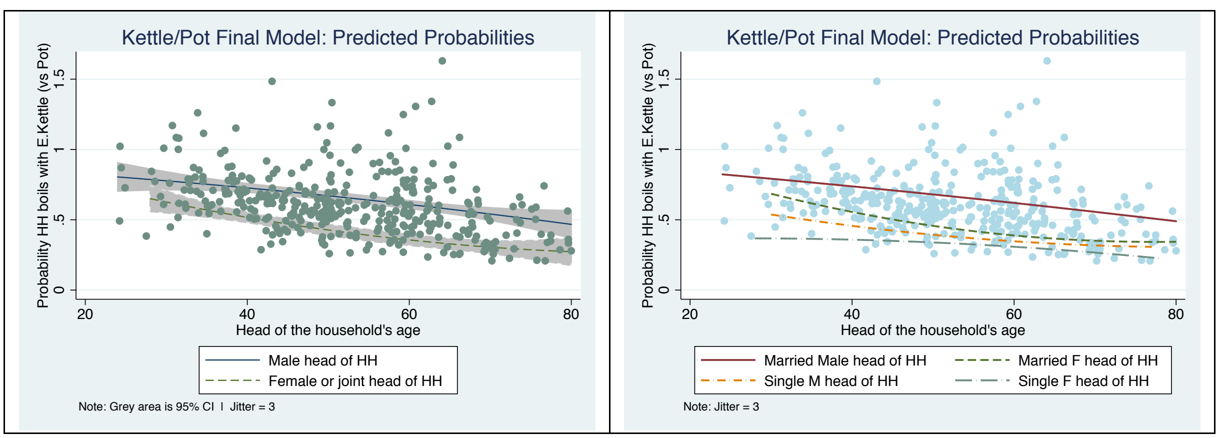

Figure 11: Predicted probabilities for using an electric kettle (vs a pot) by head of the household age, gender, and marital status

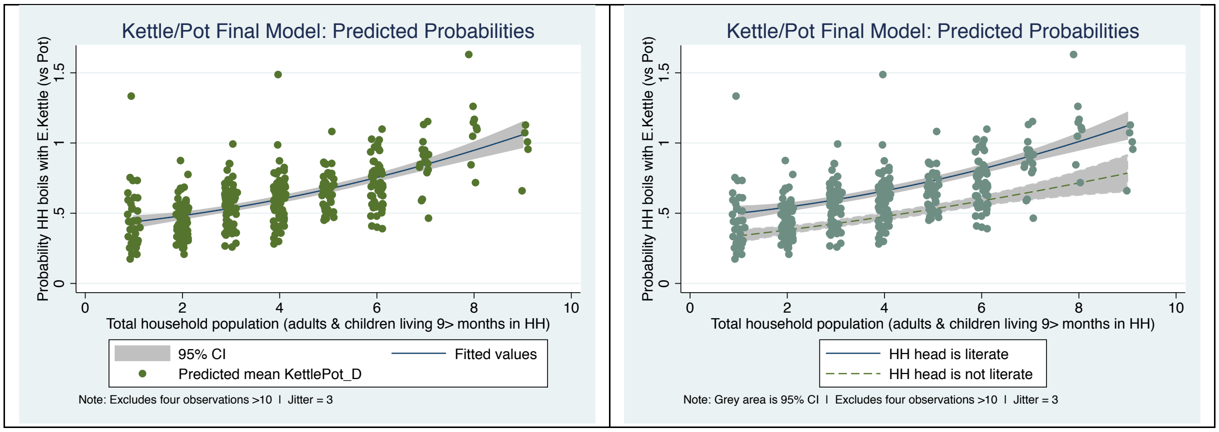

Figure 12: Predicted probabilities for using an electric kettle (vs a pot) by household size and head of the household literacy

Looking at predicted probabilities associated with household size, in Figure 11Figure 12 we see that larger households are more likely to use electric kettles as compared to smaller households which are more likely to use pots – as before, households with literate heads of household are more likely to use electric kettles across the age spectrum. In Figure 13 we examine the same trend associated with the head of the household's age and see that male-headed households are more likely to use electric kettles across the age spectrum.

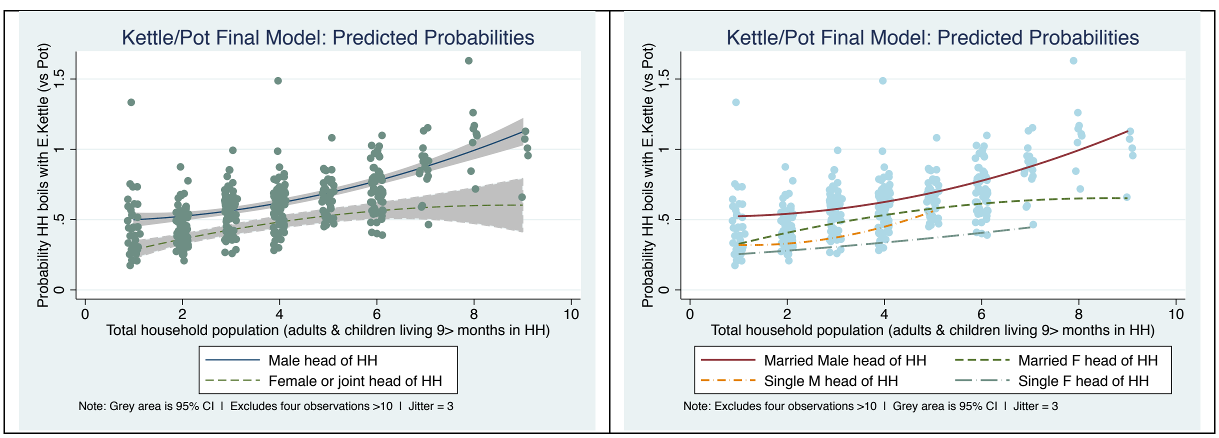

Figure 13: Predicted probabilities for using an electric kettle (vs a pot) by household size and household head gender and marital status

4. Discussion

4.1 Water quality perceptions, observations, and source classifications

Before discussing the model results and related analyses, it is useful to step-back and reflect on a few indicators of the survey data reliability. As demonstrated in previous research (Bain et al., 2014), “improved” water sources are not necessarily microbiologically safe sources – see Figure 14. Across HWT methods, improved water sources were associated with lower concentrations of TTC only in those households not treating their water (which is what would be expected since there was no intermediary step of HWT to improve source quality before drinking water samples were collected, whereas for households who boil the quality between improved and unimproved sources was quite similar – see Figure 15.

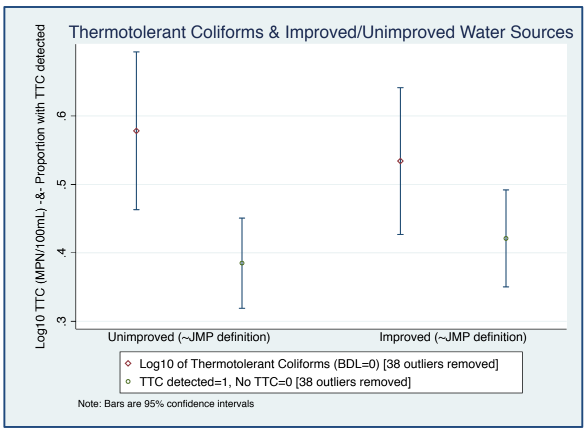

Figure 14: Thermotolerant Coliform concentrations & counts by water source

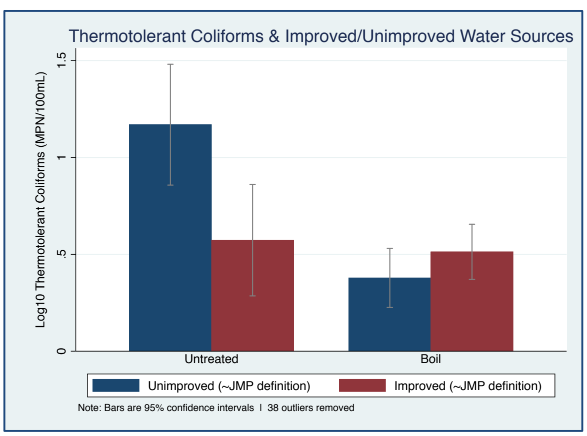

Figure 15: Thermotolerant Coliform concentrations & counts by Improved/Unimproved source across untreated and boiled water samples

Perhaps it is not surprising then that in our study we found that only 32.18% of households with improved water sources considered them to be "good" or "very good", and 56.50% of households with unimproved sources considered their water quality to be "good" or "very good". As shown above (Figure 7), TTC concentrations and counts were roughly aligned with respondent perceptions about their drinking water quality. Thus, at least in this study, one could argue that respondent's subjective perceptions of their water quality proved to be a more reliable indicator of actual microbial water quality than the improved/unimproved source classification.[3]

4.2 Associations by household size, head of the household's age, and gender

Across these models a few findings stand out. As the model indicates, we do see a relationship between household size (number of adults and children living in the home >9month/year) and rates of electric kettle and pot boiling, such that as the household population increases a likelihood of boiling with an electric kettle also increases, which boiling with pots decreases in step Figure 16. One likely explanation is that with a larger population there is more demand for bottled water and the convenience benefits of electric kettles result in higher use. As discussed in Chapter III, households with electric kettles boil more frequently than households using pots (though this relationship held even after controlling for household population, again hinting at the convenience advantage of electric kettles over pots).

As shown on the right side of Figure 16, there are higher rates of electric kettle use and bottled water use in homes with children as compared to homes with no children. This effect, however, appears to be largely driven not by the presence/absence of children but by the overall household size, and in particular the number of adults, not children, living in the home.

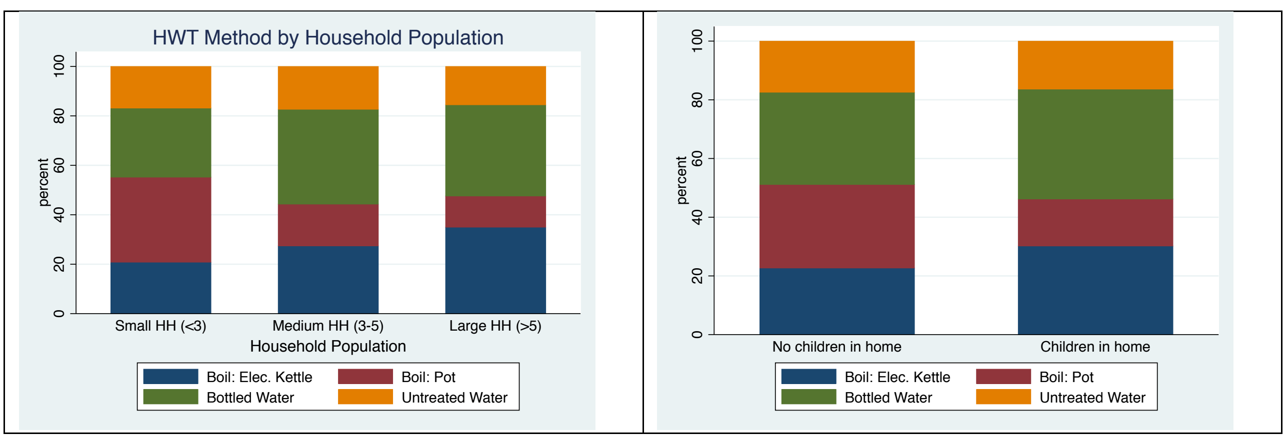

Figure 16: HWT method by household size and HWT comparison with/without children

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[3] That said, there are many situations in which contaminated water may look and taste fine when in fact it is not, as in the case of Arsenic or Fluoride contamination.

In Figure 17, we see that single female heads of households (most of whom are widowed) are the least likely to use electric kettles, with households headed by married males being the most likely.

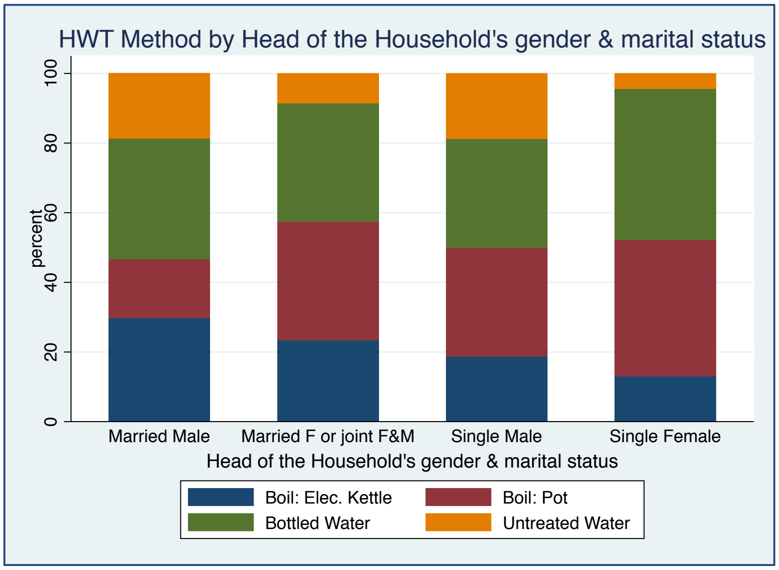

Figure 17: HWT method by head of the household's gender & martial status

Overall, across HWT methods, levels of TTC contamination are higher in female and joint female-male headed households, as shown in Figure 18; although the confidence intervals are quite large for female and joint female-male headed households and overlap with those of males headed households.

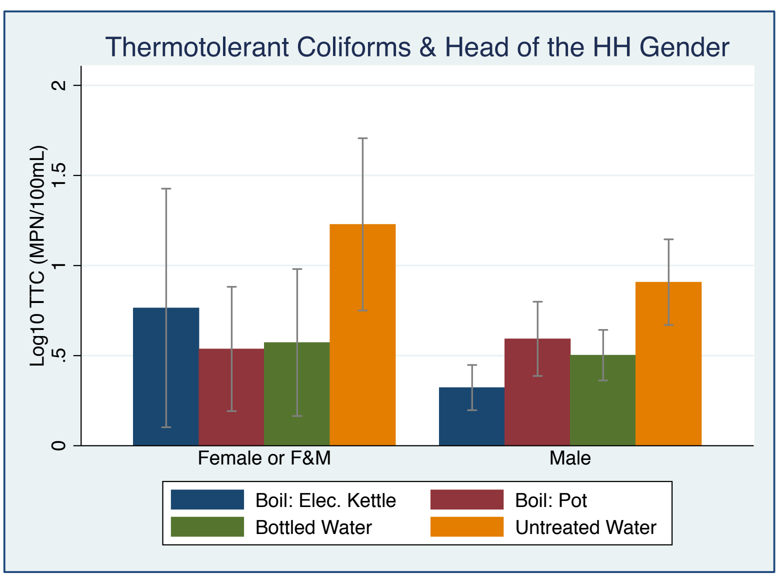

Figure 18: TTC by head of the household's gender & HWT method

4.3 Associations between village income, proxies for income/wealth, and HWT

As discussed, the village-level income data was not suitable for inclusion in these models, but it is worthwhile to reflect on the income data and related proxies all the same. Across the 15 villages, median reported annual income for 2012 was RMB 5,052 (mean=5,585, SD=1,522). As can be seen in Figure 19, most households boiling there water with pots are in relatively low income villages, which those drinking untreated water in higher income villages.

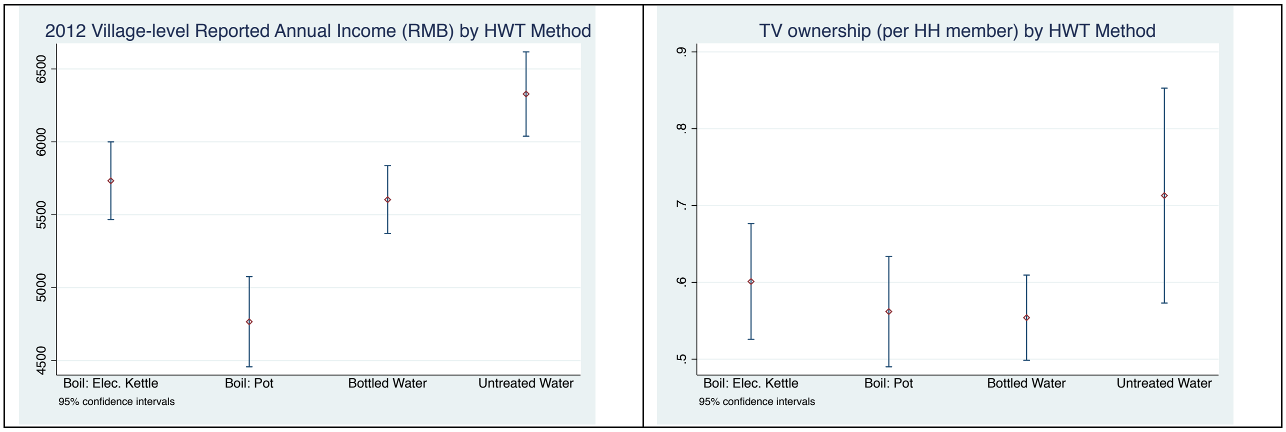

Figure 19: Reported Village-level Annual Income and TV ownership by HWT Method

If we divide Village Income into three groups (RMB 2,984-4,868 for the lower third, RMB 5,000-6,570 for the middle third, and RMB 6,630-8,526 for the upper third – with five villages in each group), we can plot the proportions of HWT use by Village Income tertile with and without the untreated group included - see Figure 20.

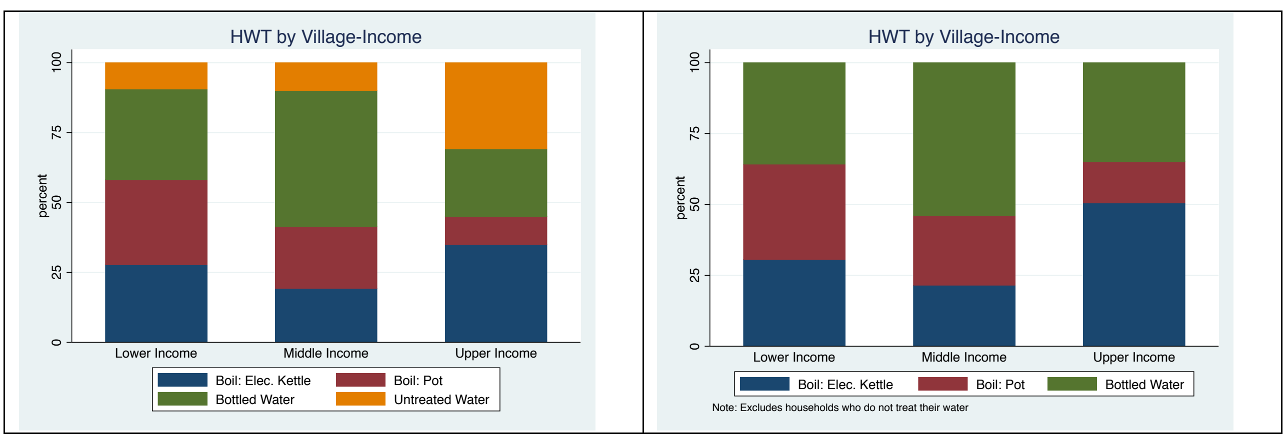

Figure 20: HWT by Village-Income (in tertiles)

The use of proxies of income and wealth (e.g., TV ownership) can be partially validated by examining associations with reported village income. On the right side of Figure 19 we see that those households not treating their water have the highest rates of TV ownership, an proxy of household wealth (and potentially income). To understand this more clearly, we can examine rates of TV ownership across reported income groups. As shown in Table 9, the rates of TV ownership are (as expected) higher among households living in higher income villages, though it appears most of the differences is between the lower income villages and the remaining upper two thirds of villages (it is noteworthy that while the mean for the middle and upper groups are essentially the same, as would also be expected the SD is smaller in the high income group).

Table 9: Rates of TV ownership, ability to afford professional care, and healthcare access by reported income

	TVs per capita per HH			% able to afford professional healthcare			Minutes to reach clinic for basic healthcare		
	Mean	**SD**	**n**	**%**	**SD**	**n**	**Mean**	**SD**	**n**
Lower Income	0.53	0.38	147	31.3	47.5	150	17.11	14.70	149
Middle Income	0.63	0.49	147	48.7	50.1	150	10.00	7.67	149
Upper Income	0.62	0.37	149	87.3	33.4	150	6.78	3.91	145
Total	0.59	0.42	443	55.8	49.7	450	11.33	10.76	443

Income Levels: Low = RMB 2,984-4,868 | Middle = RMB 5,000-6,570 | High = RMB 6,630-8,526

The proportion of households who report being able to afford professional healthcare (when/if needed) increases significantly from the lowest income group to the highest where close to 90% of households report being able to afford professional healthcare (Table 9). Similarly, we also see a clear trend (reflected in the models as well) such that access to social services such as basic healthcare are worse in lower income villages as compared to higher income villages (Table 9). Indeed, it takes significantly longer to reach a clinic that provides basic health services in the eight villages with reported incomes below RMB 5,100 (mean=13.8 minutes, SD=12.8, n=238) than it takes in the seven villages with incomes above RMB 5,100 (mean=8.5 minutes, SD=6.6, n=205) (two-sided t-test with unequal variance, $p<0.0001$).

Taken together, these data indicate that while the resolution of reported village income is indeed crude, overall it does appear to provide an accurate indicator of household income. As we saw in the model output for Boil/Untreated, the association between access to basic health services and HWT use holds even after controlling for other variables such that the longer it takes to reach a health center which provides basic health services the higher the probability that a household will boil their water versus drink untreated water – and here we see there is also an association with reported income and other proxies for income/wealth, such that poorer households are more likely to boil their water overall.

These findings also suggest that future interventions designed to promote the increased use of electric kettles in rural China would do well to analyze the impact of various subsidy levels on electric kettle adoption among lower-income populations currently using pots and solid-fuels to boil their drinking water.

4.4 Associations between village income, water source, & water quality for untreated

During the November, 2014 Groundtruthing meeting in Nanning, this association of higher rates of drinking untreated water among households in higher income villages was raised. Those CCDC staff most familiar with the villages in question explained that many households use spring water as their primary drinking water source and because this spring water is believed to be high in quality many of the households in this area do not treat their water.

Across income groups, water from a protected spring is the primary drinking water source for 37.8% of all households who do not treat their water. For those households who do not treat their drinking water in the upper income terile, 52% have protected spring water as their primary drinking water source.

As shown on the left side of Figure 21, there does appear to be an overall association such that microbial water quality is better in higher income villages as compared to lower income villages, though there is considerable variability within the income-tertile villages, as can be seen on the right side of Figure 21. As can be see in Figure 22, it appears that overall the drinking water quality is better in the higher income villages, and especially with regard to untreated samples.

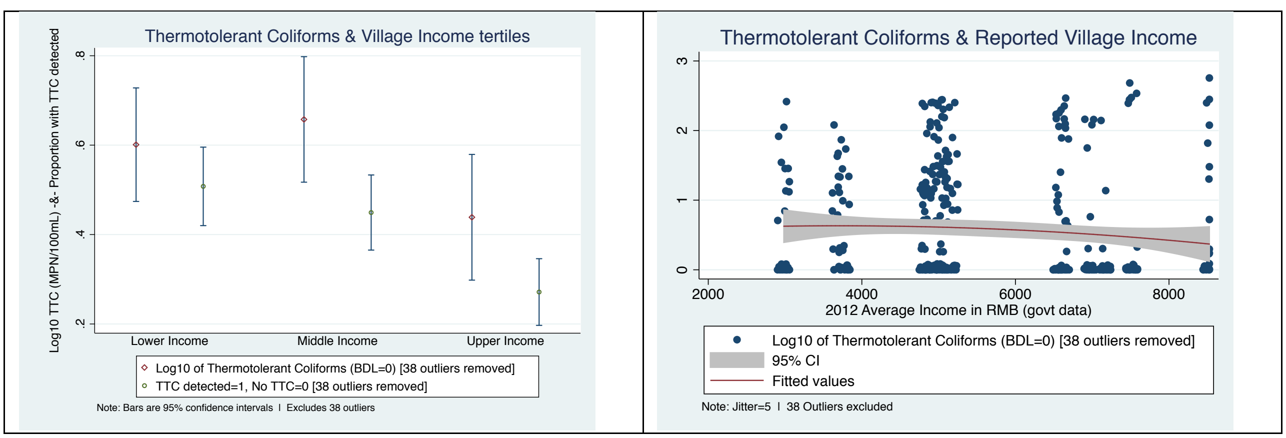

Figure 21: Reported Village-level Annual Income and Thermotolerant Coliforms

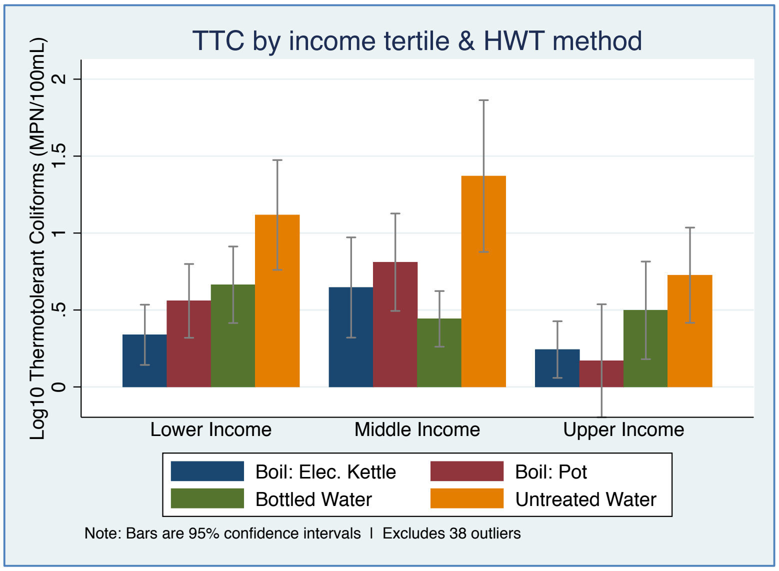

Figure 22: Thermotolerant Coliforms by income tertile & HWT method

There is some relative evidence for the anecdotal evaluation that the spring water is of good quality in these high income villages, however it can only be considered "good" relative to most of the other drinking water sources. The mean Log10 TTC for protected spring water in the upper income tertile equals 0.81 MPN/100mL (95%CI= 0.34-1.24), which is marginally better than the mean value for protected spring water across all samples (0.85, 0.44-1.25).

However, while protected spring water is one of the safer drinking water sources overall (see Figure 23), it is not safe enough to drink without treatment (according to Chinese and WHO drinking water standards).

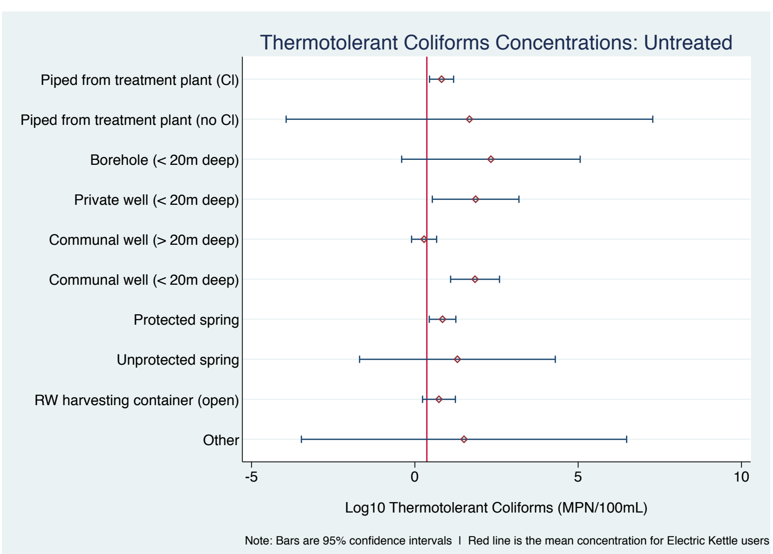

Figure 23: Thermotolerant Coliform concentrations by water source type for untreated only

4.5 Boiling time for kettles and pots (and SUMS analysis)

Before looking at the self-report data on boiling frequencies and durations we can first compare such self-report data from our winter sample with the observed data from the SUMS iButtons (temperature sensors). While, overall, the winter data sample is too small to use for the type of analyses presented here, we can still examine some of the winter data to get a clearer idea with regard to the reliability of the time-related self report data.

Using data from 44 SUMS placed on kettles and pots of varying size during the winter data collection, we see that for electric kettles (n=22) the mean recorded boiling time was 8.35 minutes and for large pots (n=9) the mean recorded boiling duration was 18.31 minutes – and the mean recorded duration for small, medium, and large pots combined was 14.5 minutes (n=23). This difference, between kettles and all pots, is significant (two-sided t-test with unequal variance, p=0.0015). Looking to observed frequencies, for electric kettles (n=22) the mean boiling frequency was 2.8 times per day, and for all pot users (small, medium, and large size pots) the mean frequency was 2.61 times per day (this is partially explained because these data were collected during the winter when the overall frequency of boiling was higher, as compared to the summer – see data below).

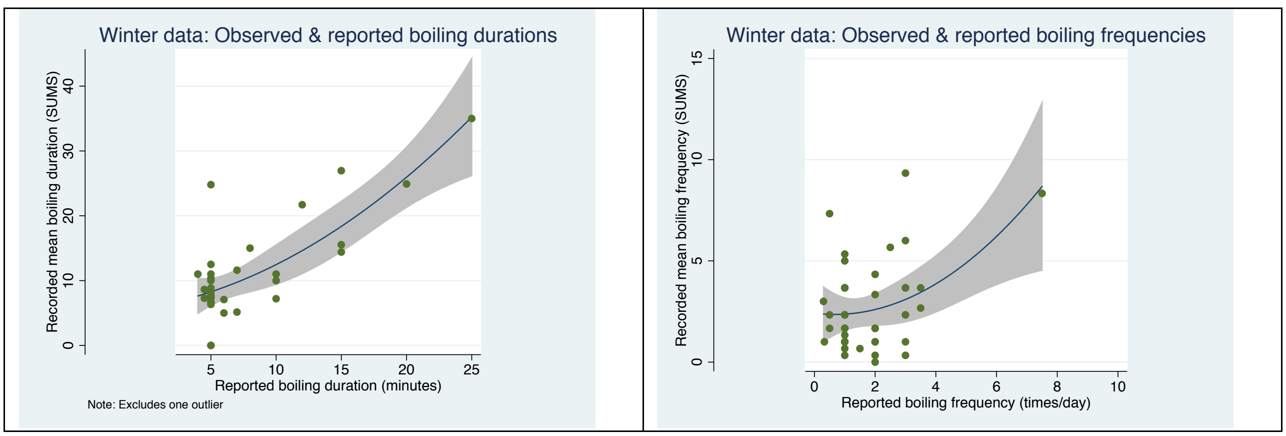

Figure 24: SUMS and self-report boiling duration and frequency data (winter data only)

As can be seen Figure 25, the agreement between observed data from the SUMS iButtons and reported data is more alligned for boiling durations than for boiling frequencies (which can be partically explained by the relatively limited 72 hours worth of data collected using the SUMS, since one would expect more time would be needed to accurately capture average daily boiling frequencies). In any case, this comparison provides additional evidence with regard to the overall accurcacy of the summer self-report data for boiling durations and frequencies.

Returning then to our summer, we can assume that for those boiling water, electric kettles should be more convenient than pots because water can be boiled at the push of a button and the fuel source need not be monitored. Across the sample, electric kettles users reported boiling an average of 2.49 times per day (SE=0.19) while those boiling with pots reported a daily frequency of only 1.39 times per day (SE=0.10); the difference is statistically significant (two-sided t-test with unequal variance, p<0.0001).

As would be expected, the frequency of boiling increases as the household population increases. This overall finding - that electric kettles boil more frequently than pot users - holds across household sizes, as can be seen in Figure 25.

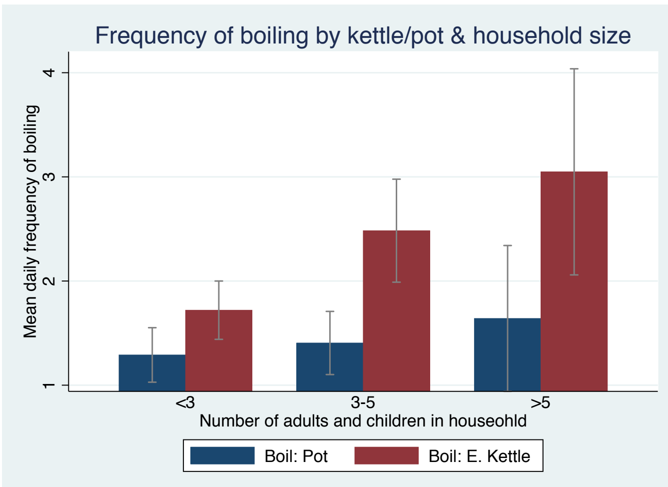

Figure 25: Boiling frequency with kettles and pots across different household sizes

Similarly, we would expect that the amount of time needed to boil water would also be less for household's using electric kettles. And indeed the difference is striking: electric kettles users reported an average boiling duration of 7.61 minutes (SE=0.48) while those boiling with pots reported an average boiling duration of 15.89 minutes (SE=1.00); here too the difference is statistically significant (two-sided t-test with unequal variance, p<0.0001).

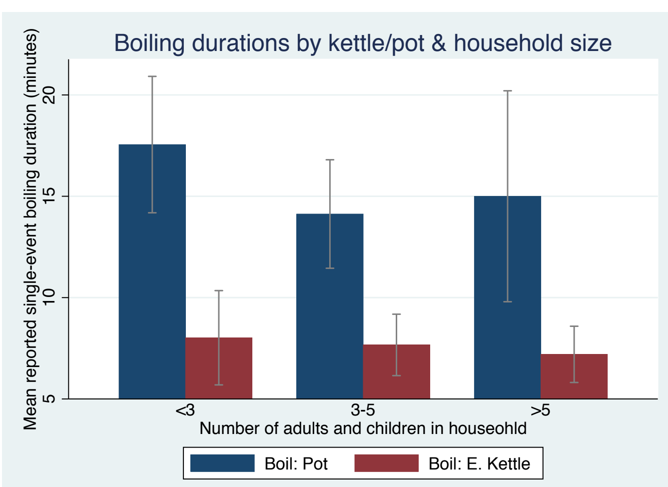

Figure 26: Boiling duration with kettles and pots across different household sizes

As something of a cross-check, we can graph the reported mean boiling duration across household size, since we would not expect to see substantial differences for electric kettle users, though for pot users households with larger populations would likely use larger sized pots to boil which would of course take longer as compared to smaller pots. As can be see in Figure 26, indeed the reported duration for electric kettles is relatively constant across household size, but, interestingly, it is the smaller households that appear to have slightly longer boiling durations (though the differences are not significant).

Taken together – that is, multiplying the reported frequencies by durations - for electric kettle users the mean total time used for boiling per day is 17.5 minutes (SE=1.24) while for those boiling with pots it is 20.5 minutes (SE=1.51); though this difference is not statistically significantly (p=0.1302, two-sided t-test). While at first glance this indicates that the total time spent boiling might be the same for electric kettle and pot users, the way the time is spent is quite different. For electric kettle users to prepare to boil they must simply fill the kettle and then turn it on, they can then use their time for other activities since the kettle's have an automatic shut-off. For those using pots, however, in addition to preparing the heat source (time-consuming for those using solid fuels, but less-so for those using LPG, for example), they must also spend some time/effort tending the pot since they must remove it or the heat source once the water is boiled. There is some evidence for this line of thinking as can be seen in Figure 27 where, as predicted, LPG users have the shortest total daily boiling duration, with those using wood reporting durations longer than the mean for all pot users.

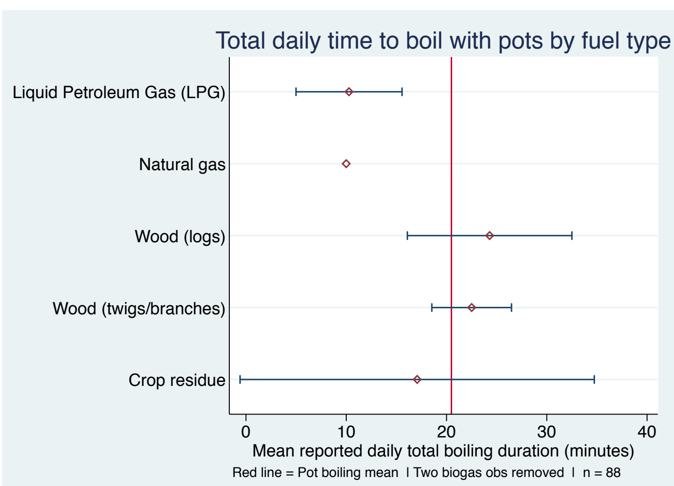

Figure 27: Total daily boiling duration for pot users by fuel type

As a final thought on these findings and discussions: among households who boil water with pots, 68% use wood/twigs/branches for fuel, and among those 68% of households (n=61), in 59% (n=36) of those homes it is females aged 15 or older who usually boil the water, and who are therefore exposure for relatively long durations to the HAP from that boiling.

5. Conclusions

Cross-references between self-reported survey data as well as observed data indicate high reliability for our household survey data overall. Similarly, while the resolution of our village-level self-reported annual income data is rather coarse, cross-checks with proxies known to be associated with income indicate that it is reliable when analyzed in tertiles.

A few conclusions stand out with regard to predictors of boiling as compared to drinking untreated water. Across models, we see that as access to basic healthcare worsens the likelihood of boiling increases. This association, however, is not necessarily based on access to healthcare and with it health-related education; rather the data suggests that this is better understood a proxy for access to services generally, and those with better access are also those living in higher income areas, where there appears to be a belief that their drinking water quality is relative good and, therefore, there is less impetus to boil it (with a large subset claiming that “spring water” quality is very good – though the TTC data suggests otherwise).

Interestingly, for female or joint male-female headed households, the probability of boiling drinking water is very high regardless of access to basic healthcare, suggesting this association is more applicable to male-headed households. Adding support to this hypothesis, we see that as rates of TV ownership increase so does the likelihood of drinking untreated water – with both TV ownership and access to healthcare being associated with higher incomes. However, for those that believe their water quality to be satisfactory or poor, they are much more likely to boil even as rates of TV ownership increase, suggesting that this perception of water quality is indeed an important, though partial, motivator behind decisions to boil or not.

Table 10: Frequency of HWT use by head of household literacy, age, and income level

Village-level income	HWT method (excludes untreated)	Head of the household is:			
		Illiterate		Literate	
		Younger	Older	Younger	Older
Low Income (n=130)	Boil: Elec. Kettle	6.9	8.5	9.2	6.2
	Boil: Pot	5.4	16.2	4.6	6.9
	Bottled Water	6.2	8.5	15.4	6.2
Medium & High Income (n=234)	Boil: Elec. Kettle	3.0	5.6	13.7	12.0
	Boil: Pot	3.8	5.1	4.7	6.8
	Bottled Water	4.3	4.3	24.4	12.4

Notes: Cell values are the percentage of households within each income group
Low Income = RMB 2,984 - 4,868 | Middle & High Income = RMB 5,000 - 8,526
Head of the household’s age: Younger = 23-52 | Older = 53-80

When we compare predictors for those boiling we see that households with illiterate older heads of household are more likely to use pots as compared to younger, literate, heads of household who are more likely to use electric kettles. As touched on above, in particular it is homes with younger, literate, male heads of household where electric kettle use exceeds pot use – and especially so in higher income villages, as can be seen in Table 10, Table 11, and Figure 28. Taken together, we see that female and joint male-female headed households have a higher preference for boiling their water generally, but most of this boiling behavior is with pots rather than electric kettles, which may be partially explained by the association between relatively lower incomes and female and joint male-female headed households, as compared to male-headed households. It is noteworthy also that in the middle income group in particular, a larger proportion of younger household heads use bottled water.

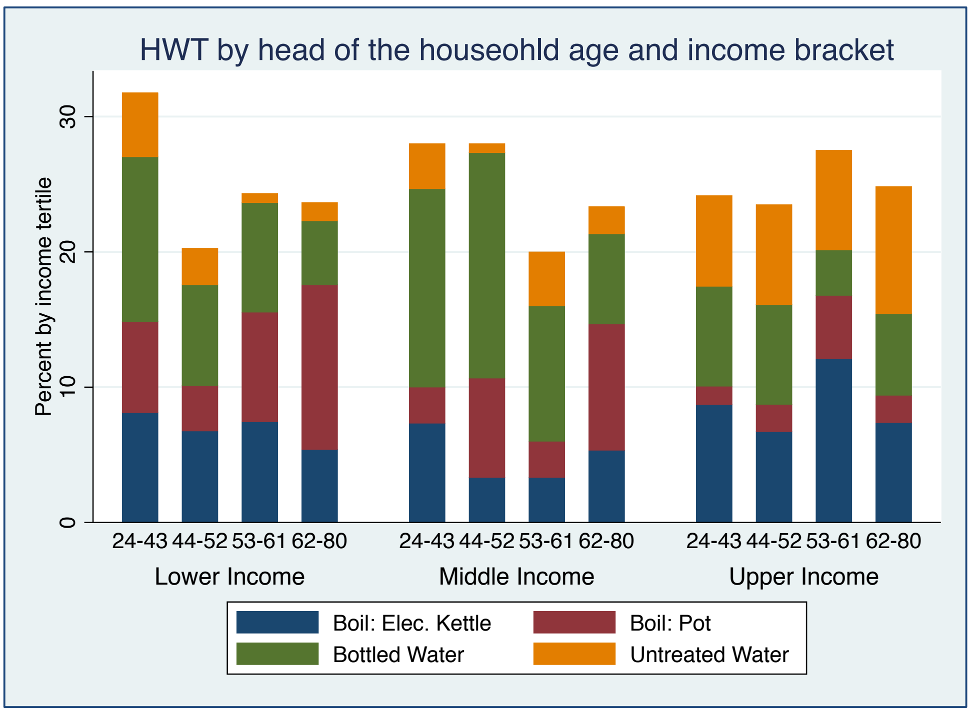

Figure 28: HWT by head of the household's age and income level

Table 11: Frequency of HWT use by head of household gender, age, and income level

Village-level income	HWT method (excludes untreated)	Head of the household is:			
		Female or joint M-F		Male	
		Younger	Older	Younger	Older
Low Income (n=132)	Boil: Elec. Kettle	3.0	3.0	13.6	11.4
	Boil: Pot	6.1	9.8	5.3	12.1
	Bottled Water	6.8	3.0	15.2	10.6
Medium & High Income (n=237)	Boil: Elec. Kettle	0.4	2.1	16.0	15.6
	Boil: Pot	0.4	2.5	8.0	9.3
	Bottled Water	3.0	2.1	26.2	14.3

Notes: Cell values are the percentage of households within each income group
Low Income = RMB 2,984 - 4,868 | Middle & High Income = RMB 5,000 - 8,526
Head of the household's age: Younger = 23-52 | Older = 53-80

With regard to the comparative advantages of electric kettles over pots, in addition to the water safety benefits discussed in the previous chapter, above we see the anticipated time savings households currently boiling with pots could gain by switching to electric kettles. This is discussed further in the Conclusions chapter.

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CHAPTER V

Bottled or Boiled?

Chapter V: Table of Contents

1. Introduction

> "Chinese reliance on bottled water as a drinking resource is a symptom of a larger and more serious disease: China's extremely polluted water resources"
>
> (Barnes and Cao, 2013: 1025)

> "With a sandwich or a motorcar, the buyer has some hope of gauging quality on his or her own, but with water, danger can be completely invisible. What is truly surprising is the extent to which, even in countries such as the UK, where people still believe their government should be responsible for social welfare (unlike the USA where a majority seem to think government only interferes with the benefits provided by free markets), people are willing to trust the bottle [i.e., bottled water] and the label to maintain the purity of nature, the private agent, more than state agencies or relatively faceless private water companies."
>
> (Wilk, 2006: 317-318)

In 2013, China surpassed the USA to become the world's largest market for bottled water, with an estimated annual consumption of 10.4 million gallons of bottled water (Rodwan, 2014). However, China's per capita consumption of bottled water in 2013 was "only" 8 gallons in 2013, slightly below the global average of 9.9 gallons; Mexico and Thailand held the top two global spots for per capita consumption, at 67.3 and 59.5 gallons per capita respectively (Rodwan, 2014). The limited available data suggest that in rural China more and more households are turning to bottled water – specifically the large 19L bottles – as their primary source of household drinking water.

My analysis in Chapter II shows that in our sample microbial contamination in bottled water is a significant problem. There are a number of pathways for such contamination. In some cases, perhaps the source water is already contaminated prior to bottling, in others contamination may be introduced at the bottling facility, in other cases re-used bottles which are improperly sterilized may be the culprit, and in other cases contamination may occur in the household – either in the bottle stand's water reservoir or, of course, after the water has been removed from the bottle (since of course there is no residual disinfectant).

One China-based study on microbial contamination of bottled water in Guangdong Province concluded that the improper sterilization of re-used bottles was the primary cause of microbial contamination (Wang, 2004). A larger study which collected bottled water samples from 2005 to 2008 found that ~11% of samples were contaminated and concluded that improved processing and packaging would likely result in a reduction in such contamination (Jia and Wang, 2009). A study in another province, however, found that bottled water improved overall from 2006-2008 (Lin et al., 2009). Though limited, these data indicate that microbial contamination in bottled water is a problem throughout China and rates and degrees of contamination no doubt vary considerably between and within provinces. As a reminder from Chapter II, in our sample 40% of bottled water samples contained thermotolerant coliforms, an indicator of fecal contamination.

With regard to chemical contaminants, again there is relatively little available research, but what data does exist suggests this too is likely a growing problem in China. One study sampled assorted brands of bottled water purchased in Beijing in 2006 and found low levels of perchlorate (an emerging contaminant) in 48% of the samples (Shi et al., 2007). A more recent study identified perchlorate in five different brands of bottled water from across China (Wu et al., 2010). A recent study analyzed samples from eight "popular brands" of bottled water in China and found varying types and levels of organophosphate flame retardants in all eight samples, though overall the concentrations were considered sufficiently low to not present a significant health hazard – and, in addition, the concentrations were lower than those of urban tap water samples (Li et al., 2014).

In this chapter, my objective is to understand which variables act as strong predictors for whether a household will boil their water or purchase bottled water. Considering the context of rural China and the results presented in Chapter II, this questions in particularly relevant since we see a relatively large proportion of poor rural households spending limiting capital on bottled water when, from a microbiological safety point of view, they could provide themselves safer water by using local drinking water sources boiled with an electric kettle (a one time, versus recurring, purchase). This analysis is also relevant when looking to future interventions which might promote safer methods of boiling such as electric kettles and face the "obstacle" of low adoption among bottled water users. In spite of the culturally engrained preference for boiled water, bottled water consumption appears to be increasing – in part because most bottled water users also heat that same water before drinking it.

Thus, this chapter can be framed in the context of a "competition" as it were between low-cost boiling and relatively high-cost bottled water, only one of which has the backing of sophisticated marketing. Results from this chapter will therefore help elucidate which populations subsets might be most likely to increase their use of bottled water in the coming years in rural China.

2. Methods

2.1 Dependent variable creation

As described in previous chapters, household water treatment (HWT) methods were classified and crosschecked against relevant survey items. As in Chapter IV, hereto a binary dependent variable (DV) was used as the outcome variable for the models described below – see Table 1.

Table 1: Binary/dummy outcome variable

DV: Variable name	Dummy coding			Observations per model		
	1 vs 0	1	0	Max possible	Ignored	Missing
BtlBoil_D	Bottled vs Boiled	157	215	372	75	3

2.1 Covariate selection

The methods employed to identify the covariates used in the modelling described in this chapter are provided in Chapter IV.

2.2 Statistical analyses and modeling

The same analyses and modeling methods described in Chapter IV were used for these analyses as well.

3. Results

3.1 Additional data on covariates used for Bottled/Boiled Modelling

For a description of the covariates used below, see Table 5 in Chapter IV.

3.2 Model results: Bottled-vs-Boiled

Table 2: Boil-vs-Untreated Modified Poisson Regression Model results by covariate block

	Risk Ratio (95% CI)			
Water & behavioral-related				
Believe DWQ is good/very good	1.19 (0.81-1.73)	1.16 (0.84-1.59)	1.03 (0.75-1.41)	0.99 (0.71-1.37)
Access to health services				
Minutes to clinic for advanced care		0.98** (0.97-0.99)	0.98*** (0.97-0.99)	0.98** (0.97-0.99)
HH can afford professional care		1.13 (0.83-1.53)	1.57** (1.15-2.14)	1.61** (1.19-2.17)
Economic indicators				
TVs in HH / HH population			0.88 (0.62-1.24)	0.97 (0.68-1.39)
Village-average price for 19L W bottle			1.06 (0.92-1.23)	1.06 (0.91-1.25)
Home can withstand severe weather			0.46** (0.29-0.73)	0.44*** (0.30-0.66)
Demographic & gender-related				
Head of the HH's age				0.988** (0.98-0.995)
HH head is male				1.02 (0.66-1.57)
HH head is married				0.97 (0.65-1.45)
HH head is literate				1.21 (0.93-1.57)
HH population (live in HH >9 months)				1.06 (0.99-1.13)
Model indicators				
Log pseudo-likelihood	-276.34	-268.46	-246.09	-228.50
n	351	347	323	307

Notes: HH=household | * p<0.05; ** p<0.01; *** p<0.001

Table 3: Boil-vs-Untreated Modified Poisson Regression Model: Full & Final models

	Risk Ratio (95% CI)		
	Full	**Adjusted**	**Final**
Water & behavioral-related			
Believe DWQ is good/very good	0.99 (0.71-1.37)	0.997 (0.73-1.40)	---
Access to health services			
Minutes to clinic for advanced care	0.98** (0.97-0.99)	0.98** (0.97-0.99)	0.98** (0.97-0.99)
HH can afford professional care	1.61** (1.19-2.17)	1.59** (1.16-2.17)	1.61** (1.18-2.19)
Economic indicators			
TVs in HH / HH population	0.97 (0.68-1.39)	---	---
Village-average price for 19L W bottle	1.06 (0.91-1.25)	1.07 (0.92-1.24)	1.06 (0.91-1.25)
Home can withstand severe weather	0.44*** (0.30-0.66)	0.46*** (0.29-0.71)	0.49*** (0.35-0.67)
Demographic & gender-related			
Head of the HH's age	0.988** (0.98-0.995)	0.987*** (0.981-0.994)	0.985*** (0.978-0.993)
HH head is male	1.02 (0.66-1.57)	1.05 (0.67-1.65)	0.995 (0.65-1.53)
HH head is married	0.97 (0.65-1.45)	0.91 (0.60-1.38)	0.93 (0.63-1.39)
HH head is literate	1.21 (0.93-1.57)	1.21 (0.94-1.55)	1.26* (1.002-1.58)
HH population (live in HH >9 months)	1.06 (0.99-1.13)	1.05 (0.99-1.12)	1.05 (0.99-1.12)
Model indicators			
Log pseudo-likelihood	-228.50	-233.46	-246.04
n	307	312	331
Notes: HH=household | * p<0.05; ** p<0.01; *** p<0.001			

For model results by block by block in isolation, see Appendix IV.

In the first model adjustment ("Adjusted" column of
Table 3), the variable for household TV ownership was removed (after performing a Wald test, see Appendix IV), because it did not appear to be contributing to the model overall (p=0.88) and because the variable on ability to afford professional healthcare also served as a proxy for income. As can be seen, its removal did not significantly change any of the RR estimates for the remaining variables.

Similarly, for the final adjustment the first variable, on perceptions of water quality (p=0.99), was removed (again after performing a Wald test); although this was a useful variable to control for, it may have been masking the impact of literacy/education on the decision to purchase bottled water since the effect size for literacy increased and the standard error decreased sufficiently for it to just meet the criteria for significance (p=0.048). An added benefit of these adjustments was that the total n for the model increased from 307 to 331.

Associations of note are that as access to advanced healthcare (and, by extension, to other services) worsens, the probability of boiling increases (RR=0.98 for each one-minute increase). The household's ability to afford professional healthcare when/if needed is a strong predictor of their use of bottled water (RR=1.6, p=0.003) – see Figure 1. This association can be disaggregated based on the head of the household's literacy, and we see that across access to advanced healthcare literate heads of households are more likely to use bottled water (Figure 1).

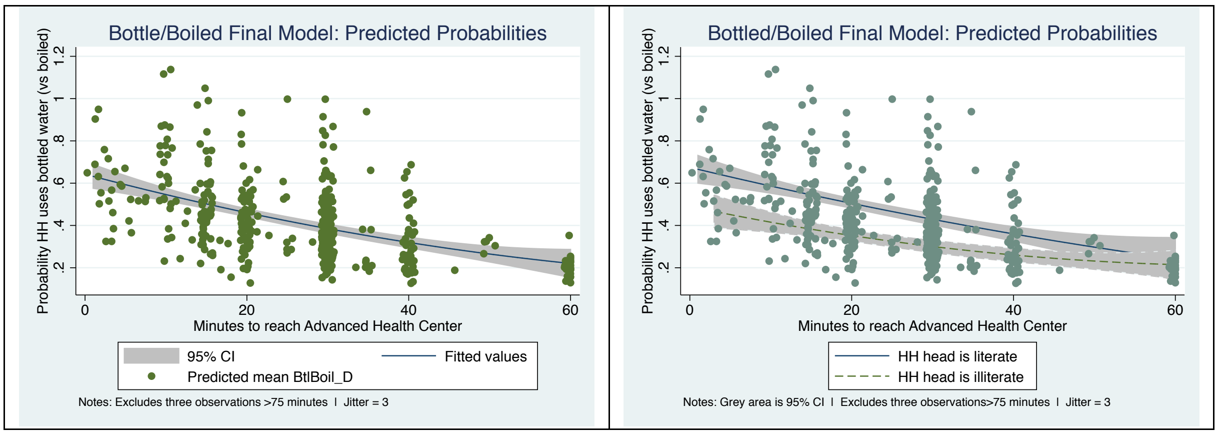

Figure 1: Predicted probabilities of using bottled water (vs boiling) by time to reach an advanced health center and head of the household's literacy

As seen in the previous chapter, there is also a strong association with the head of the household's age such that younger aged heads of household are more likely to use bottled water as compared with older household heads, and here too literate heads of household are more likely to use bottled water regardless of their age, with the exception of those older than ~65 years (where the confidence intervals start to overlap in Figure 2).

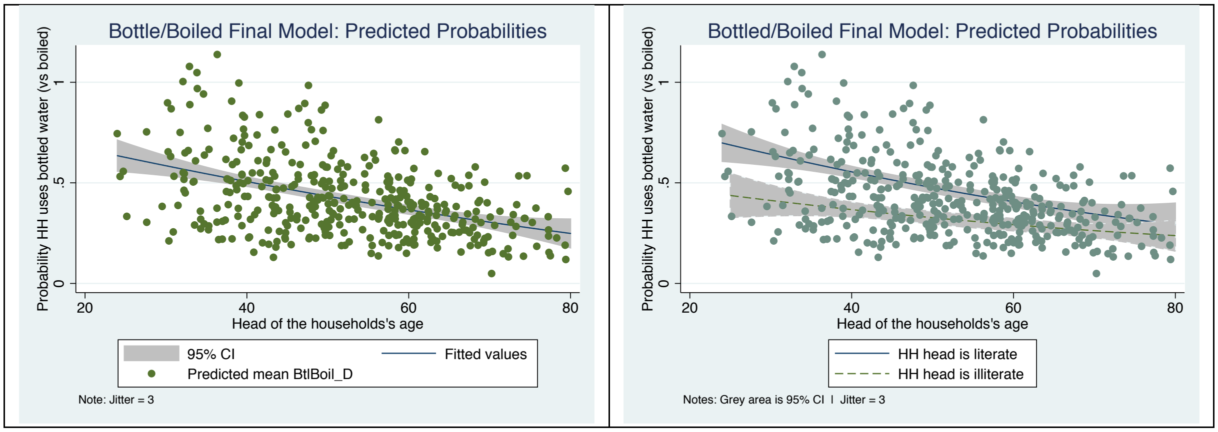

Figure 2: Predicted probabilities of using bottled water (vs boiling) by head of the household's age and literacy

The significant association with the home's ability to withstand extreme weather is at first somewhat counterintuitive, suggesting that households with higher quality homes are more likely to boil – this can be partially understood by examining inter-county differences. In County A, 83.6% and 67.5% of households that boil and use bottled water, respectively, reported that their home can withstand extreme weather; in County B, 100% of households and boil and use bottled water responded that their home can withstand extreme weather. Thus, the effect of this indicator is limited to village and household comparisons in County A.

See Appendix IV for results of sensitivity analyses.

4. Discussion

4.1 Perceived-vs-observed boiling prevalence and reasons for not using bottled water

The perception that most others around you also boil their drinking water is strongly associated with a given household's likelihood of boiling. When comparing households that boil their water to those who drink untreated water or those that drink bottled water, if the household believes "most" or "all" of their relatives boil their water, they are 1.56 times more likely to boil than drink untreated water (RR=1.56, CI=1.31-1.85, p<0.0001) and 1.36 times more likely to boil than drink bottled water (RR=1.36, CI=1.09-1.69, P=0.0039).

Overall, ~50% of households believe that most or all of their nearby relatives and neighbors boil, which is closely inline with the 48% of households in our sample who actually boil with pots and kettles, though there is considerable variation across villages (Figure 3).

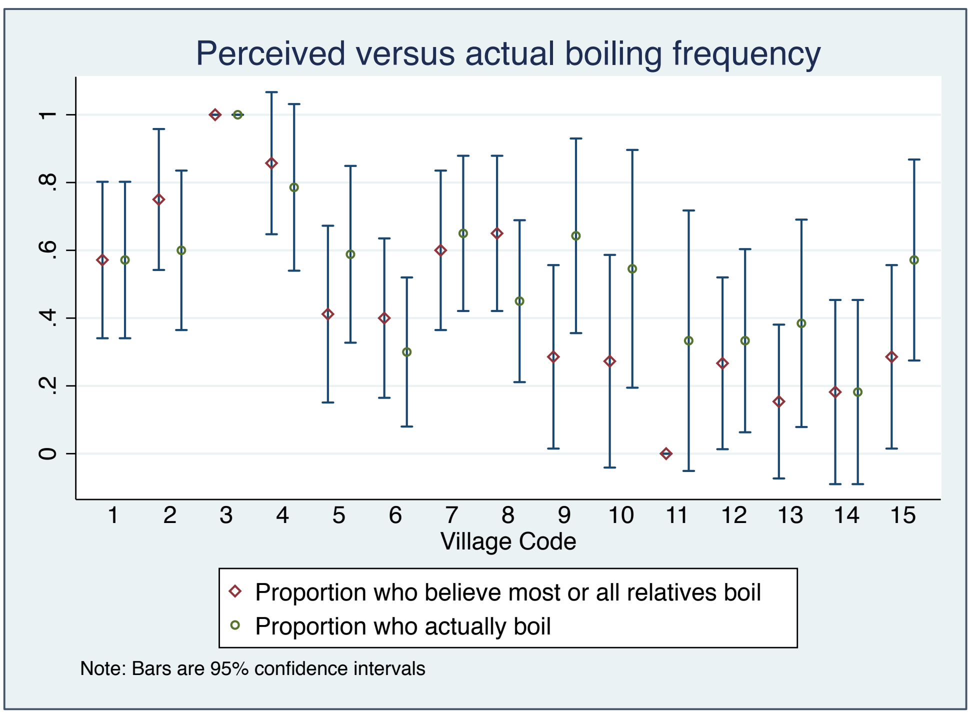

Figure 3: Comparing perceptions of boiling prevalence with reported boiling by village

Interestingly, households who boil with pots have the highest level of belief that most or all of their relatives and neighbors also boil – these proportions and their respective confidence intervals are shown in Figure 4.

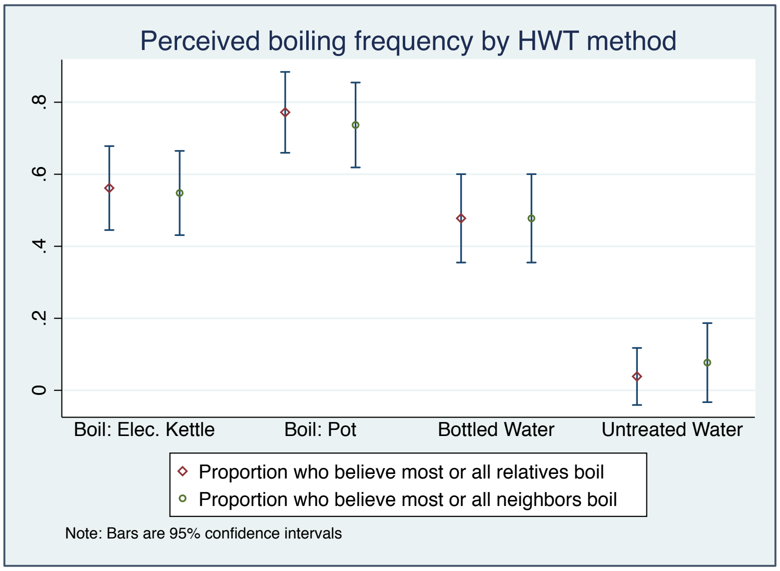

Figure 4: Perceptions of boiling prevalence among relatives and neighbors by HWT method

As can be seen in Table 4, for those households not using bottled water most reported that they find bottled water to be too expensive (37.5% overall), or that it is not convenient to get bottled water (14.3% overall). Interestingly, 13.9% reported that they do not believe bottled water is safe.

Table 4: Reasons why household does not purchase bottled water: Population proportions

(Survey Q104)	Boil (all) (n=206)	Boil: Electric Kettle (n=115)	Boil: Pot (n=91)	Untreated (n=70)	Total (n=276)
Too expensive	0.389	0.323	0.475	0.335	0.375
Not easy to get	0.168	0.150	0.192	0.072	0.143
Not safe	0.151	0.155	0.146	0.104	0.139
Don't know	0.051	0.057	0.044	0.093	0.062
Prefer spring water	0.163	0.242	0.060	0.237	0.182
Don't like or tastes bad	0.021	0.028	0.012	0.044	0.027
Not needed	0.026	0.009	0.048	0.072	0.038
Other	0.030	0.036	0.023	0.043	0.033
Totals	**1**	**1**	**1**	**1**	**1**

Note: Cells are population proportion estimates (using sampling weights)

In Figure 5, we see that a higher proportion of households with younger heads of household report that they find bottled water too expensive, which is perhaps to be expected as compared to older heads of household.

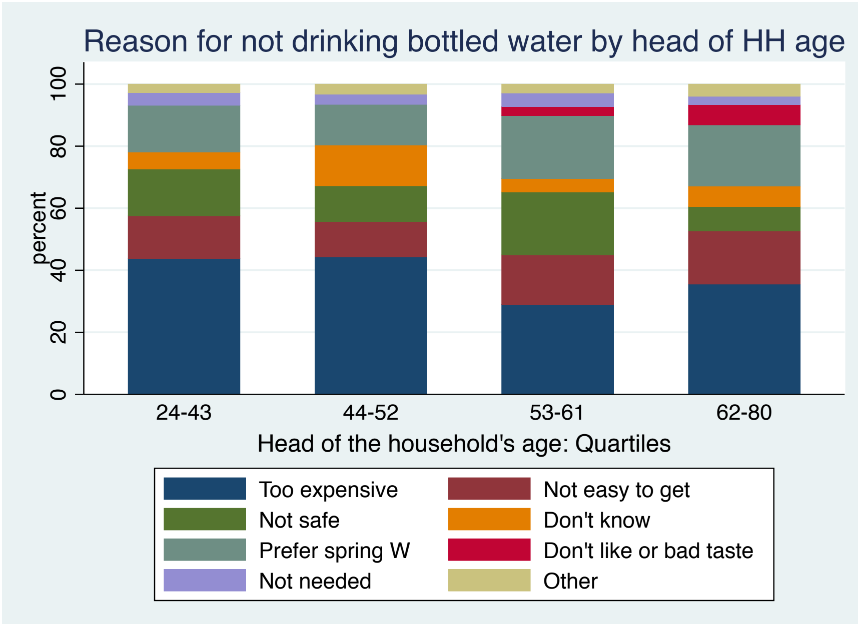

Figure 5: Reasons for not using bottled water by head of the household's age

In Figure 6, the proportion of households who feel bottled water is too expensive decreases as household size increases, and perhaps most interestingly, in Figure 7 we see that a much higher proportion of households with illiterate heads of household believe bottled water is too expensive as compared to literate heads of household. In addition, we see that literate heads of household are also more likely than illiterate heads of household to believe bottled water is not necessarily safe (a well-founded suspicion in our study area).

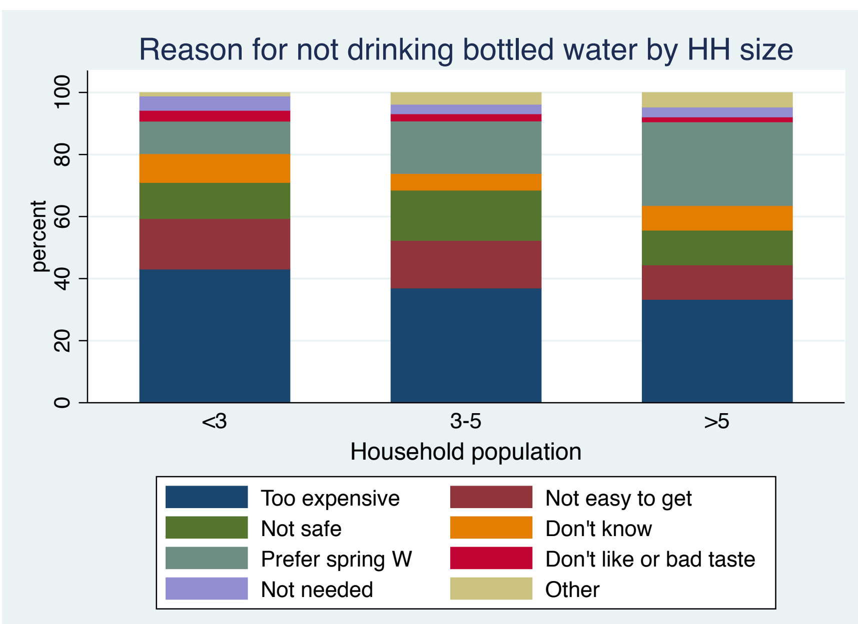

Figure 6: Reasons for not using bottled water by household size/population

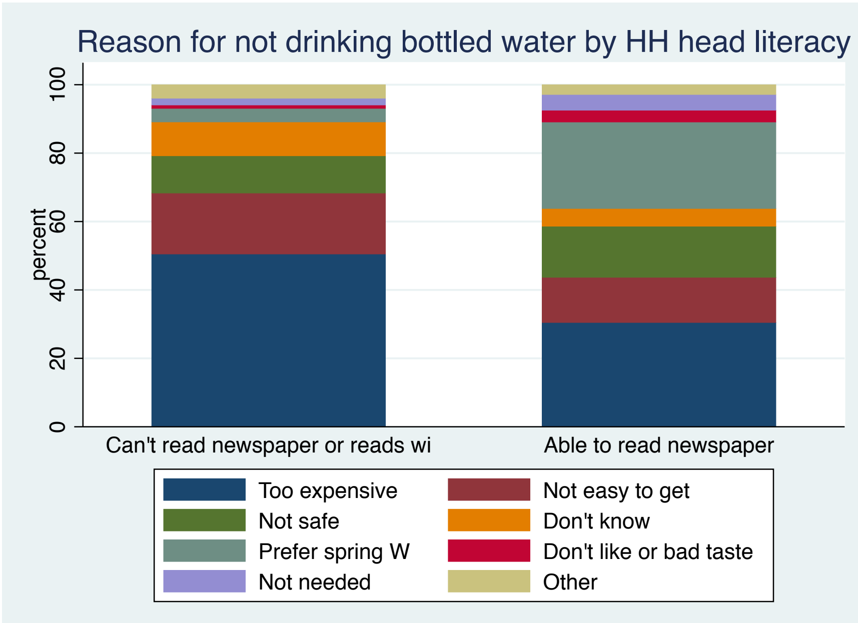

Figure 7: Reasons for not using bottled water by head of the household's literacy level

4.2 Reasons for bottled water use and relationship with bottled water quality and cost

Convenience, quality/safety, and taste are three of the top reasons provided for why rural households purchase bottled water, with the largest proportion, 46.2%, using bottled water because they believe it is "convenient" (Table 5).[1]

Table 5: Reasons why household purchases bottled water: Population proportions

(Survey Q78)	County A (n=82)	County B (n=70)	Total (n=152)
Bottled water is convenient	0.537	0.386	0.462
Bottled water is safe	0.122	0.300	0.210
Bottled water is affordable	0.159	0.043	0.101
Bottled water tastes good	0.061	0.143	0.101
Because many people drink bottled water	0.049	0.100	0.074
Tap water is poor quality	0.061	0.014	0.038
Other	0.012	0.014	0.013
Totals	**1**	**1**	**1**

Note: Cells are population proportion estimates (using sampling weights)

[1] In discussions with CCDC staff at the 2014 Groundtruthing meeting in Nanning (and also with UNICEF-China staff at a subsequent meeting in Beijing), before I shared these data CCDC and UNICEF staff both mentioned that convenience was a likely reason for the growing popularity of bottled water in rural China.

Ironically, those households who report purchasing bottled water for its perceived safety may end up consuming bottled water with the highest concentrations and rates of TTC contamination – see Figure 8 (though the differences are not statistically significant).

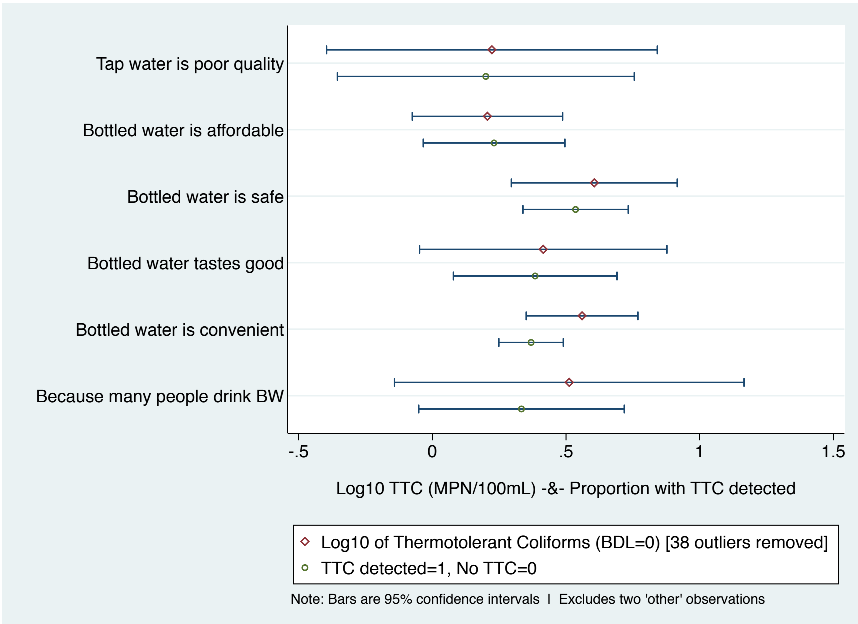

Figure 8: Reason household purchases bottled water and TTC concentrations & counts

Before examining the reasons provided for using bottled water and its cost, it is worth noting that there was no relationship between bottled water cost and quality – see Figure 9.

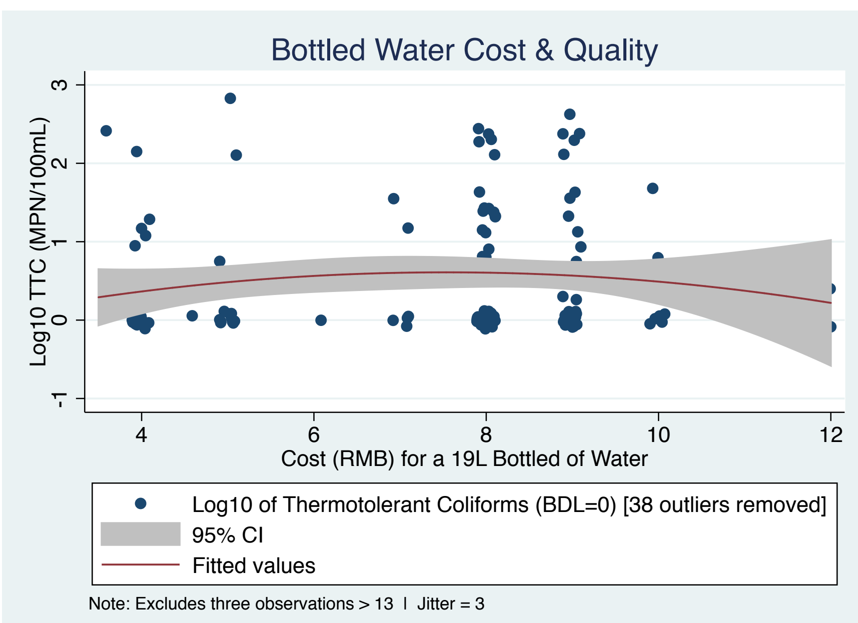

Figure 9: Bottled water cost and TTC concentrations

Looking to Figure 10, no associations with cost and reasons for use are particularly noteworthy, save that those who purchase bottled water for its affordability are slightly toward the higher side of the cost range.

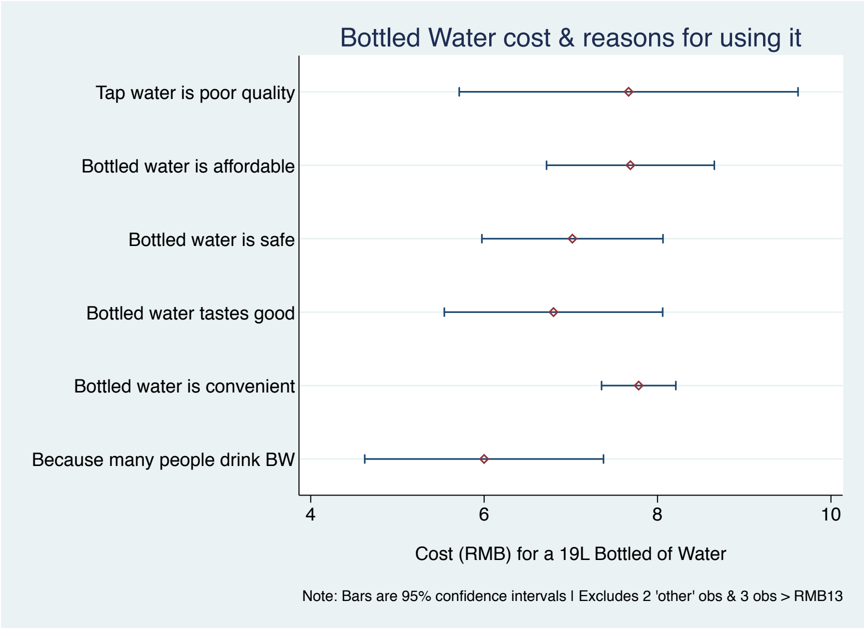

Figure 10: Reason household purchases bottled water and its cost (RMB)

One place where we do see a relationship with cost, is for those who do not use bottled water a higher proportion report not using bottled water because it is too expensive in villages where the average costs are toward the higher end, as can be seen in Figure 11, where the village-average cost of bottled water is divided into tertiles.

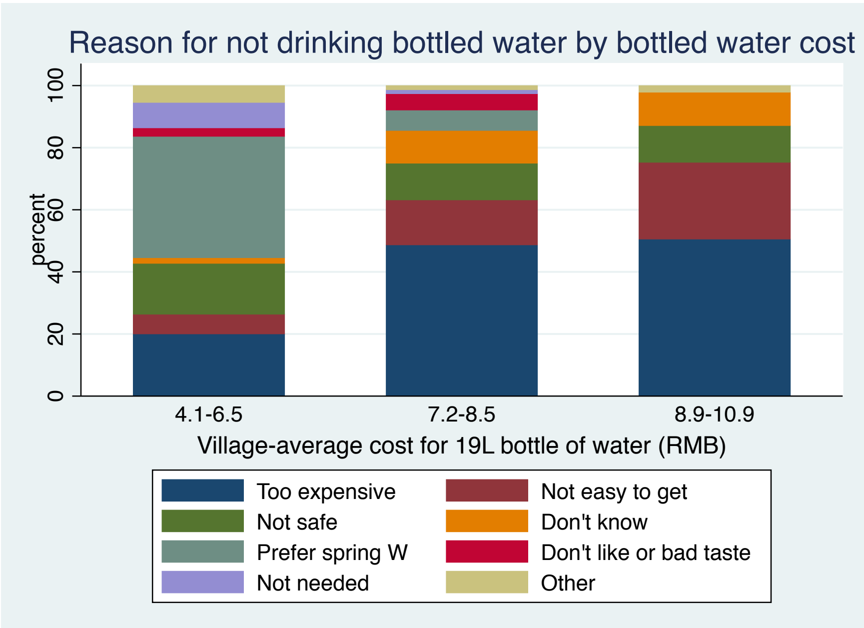

Figure 11: Reason for not drinking bottled water and village-average cost

4.3 Reasons for bottled water use, income, income/wealth proxies, and literacy

As can be seen in Figure 12, bottled water users in villages with lower incomes[2] were more likely to report purchasing bottled water because they believe the tap water was of poor quality than households living in villages with average incomes where many households believe bottled water is safe. Interestingly, we also see that among bottled water users, those who report to use bottled water because it is affordable are living in villages with mid-level incomes (Figure 12), though they are not paying especially low prices for their bottled water compared to households with other stated reasons for using bottled water (Figure 10).

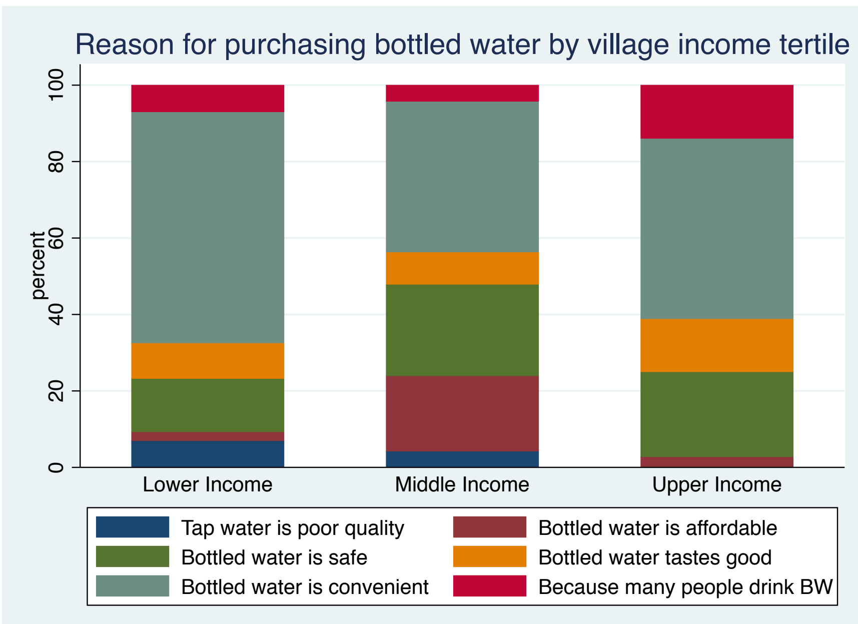

Figure 12: Reason household purchases bottled water and village income tertiles

After dividing all 15 villages into low income (reported mean annual income < RMB 5,100) and high income (> RMB 5,100), we see that the price of a 19L bottle of water was significantly lower (RMB 6.96, SD=2.32) in high-income villages, as compared to low-income villages (RMB 7.99, SD=2.29) (two-sample t-test, p=0.0072).

Figure 13 displays the proportions of reasons given for using bottled water by low and high income levels. As can be seen by comparing Figure 13 with Figure 14, the proportional breakdown of reasons given is roughly similar for those in high-income villages and those able to afford professional healthcare – indicating again, as shown in the previous chapter, that this provides a useful proxy for income.

[2] With regard to the reliability/suitability of using reported village-level income, reference the discussion and analyses in Chapter IV.

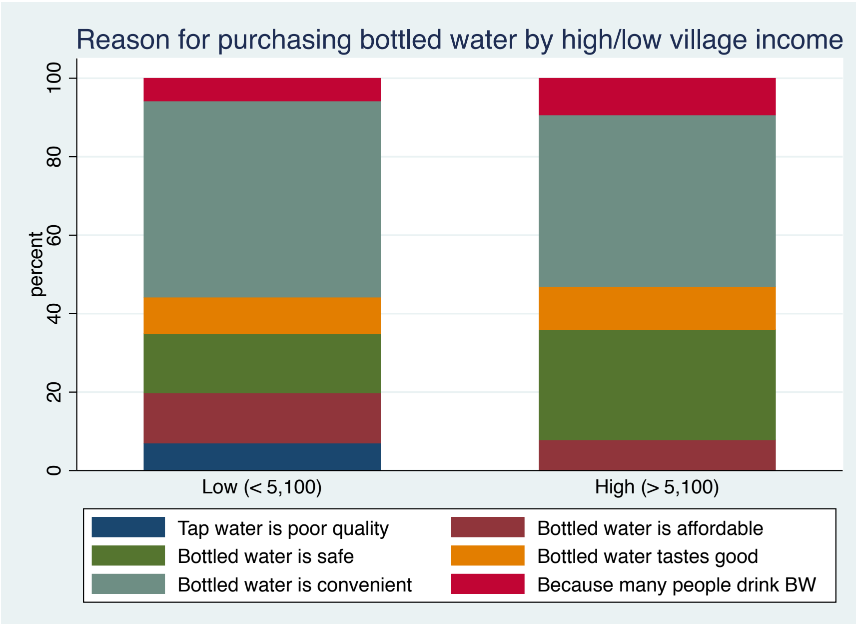

Figure 13: Reason household purchases bottled water by high/low village income

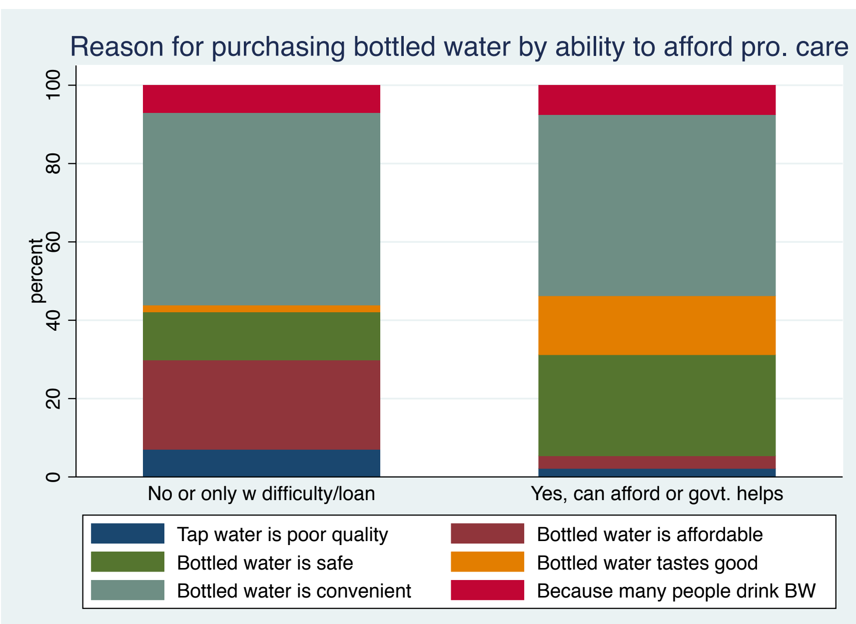

Figure 14: Reason household purchases bottled water and ability to afford prof. healthcare

4.4 Demographic and socioeconomic indicators associated with bottled water use

As also discussed in Chapter IV, we see that households with younger heads of household are more likely to drink bottled water, and conversely households with older heads of household are more likely to boil, especially with pots (rather than electric kettles) – see Figure 15. Households that boil (a more traditional approach) are more likely to have older heads of households (mean=54.04, median=55), and households who purchase bottled water are more likely to have younger heads of household (mean=49.79, median=50) (two-sample t-test, p=0.0013).

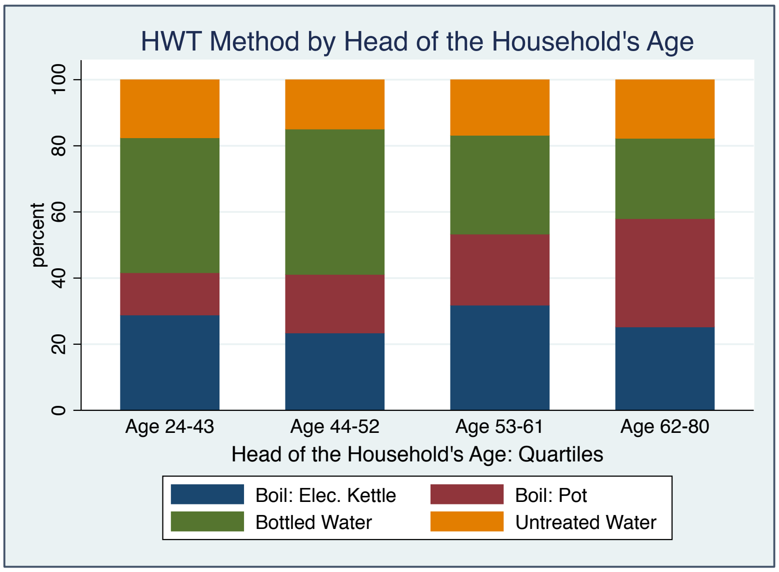

Figure 15: HWT method by head of the household's age (in quartiles)

For those households using bottled water, when comparing the reasons given by head of the household's age, older heads of household tend to purchase bottled water because it is convenient or perceived to be safe (Figure 16).

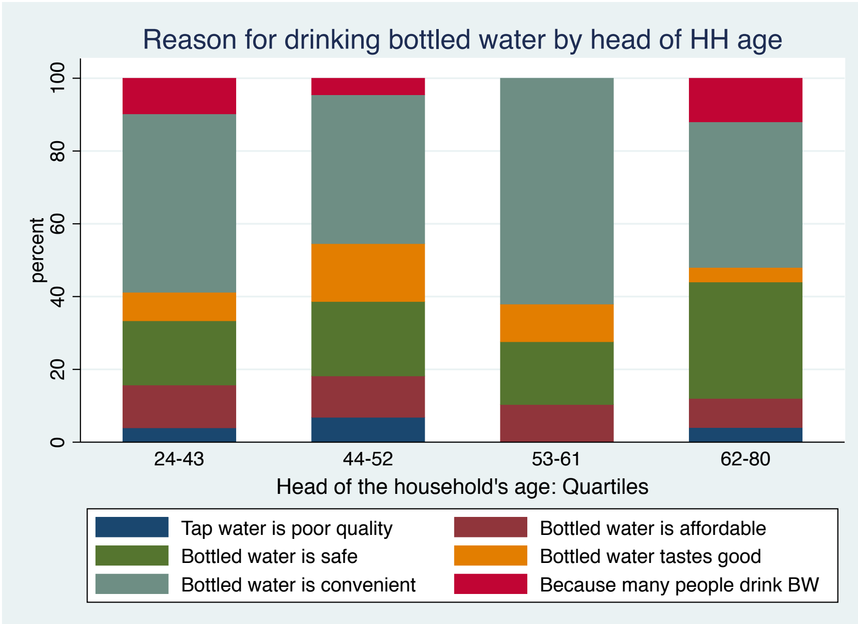

Figure 16: Reason household purchases bottled water and head of the household's age

In Figure 17, we see that where the head of household is illiterate, a far greater proportion of households purchase bottled water for its perceived convenience, as compared to literate heads of household.

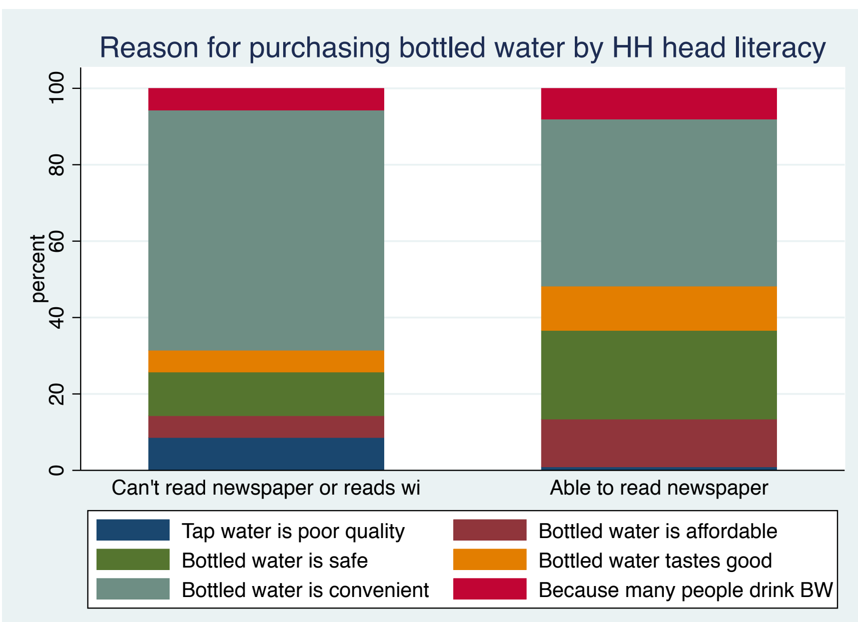

Figure 17: Reason household purchases bottled water and head of the household's literacy

Given the importance of perceived convenience, it is noteworthy that within the bottled water users group, the proportion of respondents citing the convenience benefits of bottled water does not increase in step with household size, since one might expect larger households would be more drawn to bottled water for its convenience. However, while the mean household population among bottled water users for those citing convenience is 4.18 people (SD=1.95) and lower than the bottled water overall mean household size of 4.22 (SD=2.05), looking across the three primary HWT methods, the mean household size is largest (4.22 people) among bottled water users, with households that boil and that drink untreated have close to 3.8 people on average (3.57 and 3.8, respectively).

What is more interesting still, is that when boiling is broken into electric kettles and pots, the mean household size for electric kettle users is almost as large as that of bottled water users (Figure 18) – hinting perhaps at the partial effect on overall preference for more convenient methods of drinking water treatment in larger households.

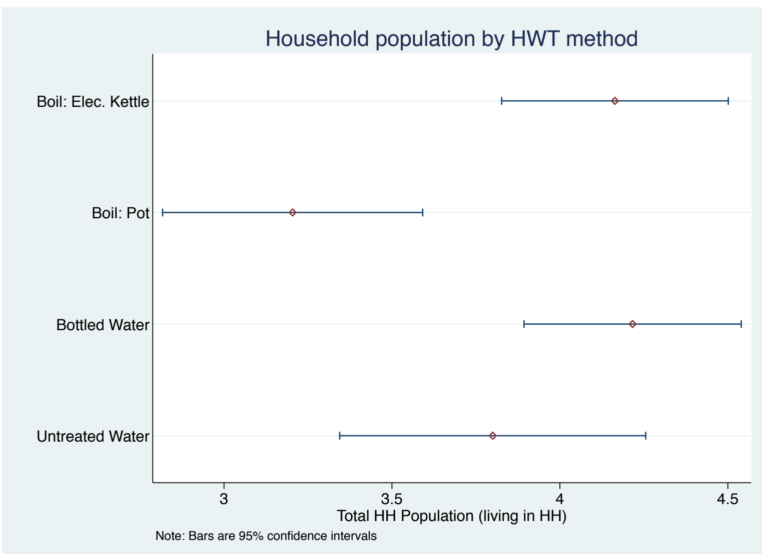

Figure 18: Total household population by HWT method

5. Conclusions

While research on consumer preferences for bottled water in high-income countries suggests that many purchase bottled water because of its perceived superior taste and quality (and related health benefits) as compared to tap water (e.g., Doria, 2006), at least in this area of rural China the primary motivating factor appeared to perceptions of bottled water's convenience.

Overall, these data, as well as the findings presented in the previous chapter (see especially Tables 10 & 11), suggest that households with relatively younger, more literate, heads of households (and likely higher incomes) are more likely to buy bottled water, often for perceived convenience. Ironically though, households purchasing bottled water for its perceived safety ended up with relatively contaminated bottled water as compared to households purchasing it for other reasons – and especially to households boiling with electric kettles (see Chapter III).

Perhaps it is not so surprising that in higher income villages bottled water is less expensive as compared to lower income villages, reflecting the overall improved access to goods and services often associated with higher incomes. The finding that there was no association between bottled water cost and quality may be in part due to the overall lack of higher quality, large-brand, bottled water in these areas. However, based on evidence from other countries it is not surprising that quality does not increase in step with price. Indeed, this lack of an association between quality and price for products such as bottled water is not a new phenomenon (Gerstner, 1985).

As important as it is to understand why current bottled water users prefer bottled water, looking to the future it is prudent to try and understand the barriers to the growth or decline in bottled water use in rural China. Looking back to Table 4 and only at those households boiling with pots, close to half (47.5%) do not use bottled water because they believe it is too expensive and 19% responded that it is not easy to get. These findings suggest that the use of bottled water in rural China will likely increase as more and more households are better able to afford bottled water and have easier access to it.

Taken together these findings suggest more and more rural households will purchase bottled water and end up with drinking water with lower microbiological quality than rural households choosing to use electric kettles to boil locally sourced and/or local utility water. With regard to the promotion of electric kettles and potential uptake among rural households, those currently purchasing bottled water for its perceived convenience will likely continue to do so, but those using bottled water for its perceived safety may well be convinced that their goals are more reliably, and much more cheaply, achieved by using electric kettles to boil their water (context and microbiological and chemical source water quality depending).

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Chapter VI

Conclusions

Chapter VI: Table of Contents

1. Introduction

"我国农村饮用水和环境卫生状况，从整体上看还存在诸多问题，与国家经济社会的快速发展不相适应，与社会主义新农村 建设的要求不相适应，与广大农民改善健康状况，提高生活质量 的迫切需要不相适应。"

"With regard to the overall drinking water and sanitation situation in rural China, there are still many problems and the current situation is at odds with the country's rapid economic and social development, the requirements for constructing a New Socialist Countryside [a government initiative announced in 2006], and the urgent need to improve the health and living standards of most rural residents."

(Tao, 2009: 2 [my translation])

"Charity-oriented and other paternalistic programs may ease the pain for a few in the short run, but they are totally inadequate to lift entire nations or communities out of poverty… Social protection programs should be generous enough to enable poor people to survive shocks *and* build assets to lift them out of poverty."

(Narayan et al., 2009: 22)

"For gains in human development, and improvements in the lives of the poor, investments in rural water have few rivals."

(UNDP, 2006: 86)

This research sought to better understand the household water treatment (HWT) methods used in rural China, their relative effectiveness, and the factors that appear to predict their use. At its onset, the underlying motivation driving this research was a desire to better understand the barriers to HWT adoption, with the hopes that such knowledge would allow for the successful promotion of a HWT method which would in turn expand safe water access in rural China until the time when all rural residents had access to safe, piped, drinking water.

The finding that so many rural households use electric kettles, and that this HWT method (hitherto essentially undiscussed in the HWT literature) might be the sought after vehicle for expanding safe water access, with additional benefits, was an unexpected finding indeed. Far more challenging, was the attempt to understand which factors predict the preference of electric kettles over boiling with pots, purchasing bottled water, or not treating their water at all.

2. Summary of research findings

While less than half of all households have piped water from small-scale utilities, nearly all households (97.6%) reported having some sort of piped source of water in their home or courtyard (from utilities, rainwater harvesting cisterns, wells, boreholes, etc.). Reported two-week diarrhea incidence was relatively low at 3.8% of all households

With regard to HWT, prevalence estimates for the population studied in rural Guangxi are that 47.5% (95% CI=37.7-57.2) of households regularly boil their water (any method), 34.4% (95% CI=22.2-46.5) drink bottled water (with more than half usually heating the bottled water via a heating-unit inside the bottle stand), and the remaining 18.2% (95% CI=11.3-25.0) do not treat their drinking water. Disaggregating the 47.5% of boilers, I estimated that 20.3% (95% CI=11.5-29.1) of households boil with pots and 27.1% (95% CI=17.2-37.0) boil with electric kettles.

Among the HWT methods, Thermotolerant Coliform (TTC, an indicator of fecal contamination) counts and concentrations were the lowest for households boiling with electric kettles: TTC was detected in only 28.4% of such households, and geometric mean TTC were 73% lower than households with untreated water. Overall, compared to households using electric kettles, households that did not treat their water were twice as likely to have TTC detected (risk ratio=2.03, $p<0.001$). These findings from the summer data collection were reflected in the winter data results as well.

After using a series of multilevel mixed-effects linear regression models to control for the influence of likely confounders and intermediaries, as well as the impact of clustering and other covariates we expect could impact drinking water quality, HWT was consistently and significantly associated with Log_{10} TTC reductions as compared to households drinking untreated water. Across these models, boiling with electric kettles was consistently associated with the largest Log_{10} reductions (>0.55, $p<0.001$), with bottled water and boiling with open pots showing smaller Log_{10} TTC reductions.

Looking at predictors of HWT use, across results from multiple series of modified Poisson regression models (with a log link for binary outcomes and cluster-robust standard errors) a few conclusions stand out. With regard to predictors of boiling as compared to drinking untreated water, as access to basic healthcare worsens the likelihood of boiling increases. This access may be understood as a proxy for access to services generally; those with better access are also those living in higher income areas.

For female or joint male-female headed households, the probability of boiling drinking water is very high regardless of access to basic healthcare, suggesting this association is more applicable to male-headed households. Households who believe their water quality is satisfactory or poor are much more likely to boil, even as rates of TV ownership increase, suggesting that this perception of water quality is indeed an important motivator behind decisions to boil or not, and not significantly modified by income/wealth.

When we compare predictors for those boiling with electric kettles versus pots and solid-fuels, we see that households with illiterate older heads of household are more likely to use pots as compared to younger, literate, heads of household who are more likely to use electric kettles. In particular, it is homes with younger, literate, male heads of household where electric kettle use exceeds pot use – and especially so in higher income villages.

Looking at predictors of drinking boiled water versus bottled water, the perception that most others around you also boil their drinking water is strongly associated with a given household's likelihood of boiling. When comparing households that boil their water to those who drink untreated water or those that drink bottled water, if the household believes "most" or "all" of their relatives boil their water, they are 1.56 times more likely to boil than drink untreated water (RR=1.56, CI=1.31-1.85, $p<0.0001$). For those households not using bottled water, most reported that they find bottled water to be too expensive (37.5% overall), or that it is not convenient to get bottled water (14.3% overall); 13.9% reported that they do not believe bottled water is safe.

Convenience, quality/safety, and taste are three of the top reasons provided for why rural households do purchase bottled water, with the largest proportion, 46.2%, using bottled water because they believe it is "convenient". Given the importance of perceived convenience, it is noteworthy that within the bottled water users group, the proportion of respondents citing the convenience benefits of bottled water does not increase in step with household size (since one might expect larger households would be more drawn to bottled water for its convenience).

Taken together, the data suggests that households with relatively young, more literate, heads of households (and likely higher incomes) are more likely to buy bottled water, often for perceived convenience. Ironically, households purchasing bottled water for its perceived had relatively contaminated bottled water as compared to households purchasing it for other reasons.

In higher income villages bottled water is less expensive as compared to lower income villages, reflecting the overall improved access to goods and services often associated with higher incomes. There was no association between bottled water cost and quality.

3. Implications for future research

In the water, sanitation, and hygiene (WASH) field, this was the first China-based study I am are aware of to disaggregate HWT methods and evaluate their impact on microbial contamination in drinking water. This is also the first study I am aware of to identify the comparative effectiveness of boiling with electric kettles as compared to boiling with open pots. Similarly, this was the first study I am aware of to examine and model the socioeconomic predictors of HWT use in China.

As discussed in the first chapter, of the principal reasons HWT interventions continue to achieve low levels of adoption is because the socio-cultural and behavioral aspects of HWT adoption are not sufficiently accounted for (Figueroa and Kincaid, 2010, Mosler, 2012). Results from a recent systematic review of 1,551 “peer-reviewed research article written in English on one or more of the point-of-use water treatment [aka, HWT] interventions” found that “less than 2% of published papers that were identified by our search described research on behavioral factors influencing adoption” and only a few clearly specified the theoretical rationale used or provided sufficient methodological details to allow for replication (Parker Fiebelkorn et al., 2012: 625).

What relatively little research there is on the subject suggests that reasons for adoption are highly context-specific and are often not based on an understanding of germ theory, perceived health risks or links with diarrhea. In short: “The field of water, sanitation and hygiene lacks a theory-based approach to the design and evaluation of interventions” (Figueroa and Kincaid, 2010: 3) and this in turn hampers the successful promotion of HWT. Additional research on these socio-cultural-behavior factors as well as political factors, at multiple levels (policy, community, household, and intra-household), is therefore needed to better understand how to improve HWT promotion efforts. This research is a step in that direction for rural China, and will hopefully prove useful for researchers in other countries as well.

This research also highlights the promise of electric kettles as a HWT method. A recent Annual Review paper on “Safe drinking water for low-income regions” concluded that “Despite existing advocacy of household water treatment methods to mitigate both microbial and arsenic contamination, the literature suggests that most HWT-based systems, with the possible exception of boiling, are unlikely to be transformative at larger scales” (Amrose et al., 2015).

However, unsafe boiling has clear drawbacks. Presently, most rural households in China use wood, agricultural biomass, or coal to boil water, the combustion of which creates household air pollution (HAP). As discussed already, HAP exposure, like cigarette smoke exposure, causes a number of cardiovascular and pulmonary cancers and other diseases (Chafe et al., 2014, Zhang and Smith, 2007, Smith et al., 2000, Zhang and Smith, 2003).

There is growing recognition globally of the extreme negative health impacts caused by HAP exposure. Indeed, in recent years HAP was identified as one of the primary environmental causes of premature death globally, with 3.9 million attributable deaths in 2010 (Smith et al., 2014). HAP and black carbon emissions also exacerbate climate change (Bonjour et al., 2013, Ramanathan and Carmichael, 2008). What is more, as discussed, once boiled water cools it is susceptible to secondary microbial contamination if not properly stored (Wright et al., 2004).

Electric kettles may offer a partial solution to these interrelated problems. As this research revealed, households using electric kettles had the safest drinking water and the lowest risk of having TTC detected. What is more, electric kettles should provide reliable and full pathogen inactivation, limited opportunity for secondary-contamination (because most electric kettles in rural China will not function unless the lid is closed), and – importantly - no HAP.

The convenience benefits are clear. Electric kettles are automatic, so once turned on they heat the water until it boils and then automatically shut off. This means boiling water on demand is easy and convenient, and the water should reach ~100C; this in contrast to boiling with open pots which are more labor intensive, and the water is not always brought to a boil. What is more, it is easier to boil smaller quantities of water with an electric kettle than a pot due to the convenience of pushing a button.

Considering the challenges inherent in achieving sustained HWT adoption generally, for low and middle income countries with relatively high rates of rural electrical connectivity (or where solar cells are an option), safe boiling with electric kettles may be a pragmatic option for expanding safe drinking water access in poor rural areas. I believe more research in this area is needed.

4. Implications for China and other countries

Other than boiling, the only other "HWT" adopted globally at such a scale is bottled water: an environmentally unsustainable product backed by highly effective marketing with continued and rapid growth in low and middle-income countries such as China.

As demonstrated in this research, bottled water is not necessarily even a safe drinking water source. What is more, many of these poor rural households are spending money to purchase bottled water of no better quality than could be obtained with a one-time purchase of an electric kettle (equivalent to forgoing approximately seven 19L bottles of water).

For households boiling with pots in this study, close to half (47.5%) do not use bottled water because they believe it is too expensive, and 19% responded that it is not easy to get. Looking to the future, these findings suggest that the use of bottled water in rural China will likely increase as more and more households are better able to afford bottled water and have easier access to it. Taken together these findings suggest more and more rural households will purchase bottled water and end up with drinking water with lower microbiological quality than rural households choosing to use electric kettles to boil locally sourced and/or local utility water.

Looking to the coming years and likely shifts in HWT trends in rural China, it is fair to say that hundreds of millions of rural Chinese are facing, in effect, a choice between bottled water or boiling. As one author put it, bottled water is "…the ultimate absurdity: the waste and inequality of the bottled-water trade. Here we have a world with acknowledged ecological problems, rising energy prices, and global climate change, where a significant amount of energy and materials are being expended to transport water to places that already have plenty of it, freely available. Then there are the billions of plastic bottles manufactured and then discarded, littering the land and ocean, or being buried in landfills or incinerated at public expense"(Wilk, 2006: 319).

Though this author was writing from a high-income country perspective, much of this "absurdity" applies equally well to China, a solidly middle-income country with large scathes of low-income rural areas.

Given the well-documented problems with HWT adoption (Waddington et al., 2009), rather than introducing new HWT technologies, the most practical way to expand access to microbiologically safe drinking water in rural China may be to build upon the existing preference for boiled water (and safety concerns around drinking water), and promote the expanded use of electric kettles. Hopefully, findings from this research can be used to elucidate a path forward.

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Appendix I

Household Surveys

Notes:

Some of the original MPAT Household Survey questions were deemed too "sensitive" by the IRB in Beijing and/or CCDC officials, and were therefore removed from the surveys; hence the skips in question numbering below. The full, original, surveys are available at www.ifad.org.mpat.

Survey questions 80, 101, and 105 were adapted from a World Bank Household Survey used in India; questions 86, 94, and 95 were adapted from Mosler (2012) and Huber (2011); I developed and tested questions 84, 88, 93, 97, 98, and 107 while working in rural Kenya in 2011 (for the NGO Nuru International); and questions 89, 90, 91, and 92 were adapted from WHO (2012).

The English version of the survey is provided below, followed by the Chinese version.

(All of the appendices are presented using "courier" font.)

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[MPAT] Household Survey			**IFAD**
Enumerator: ____________	Time _____:_____ to _____:_____	Date (YY/MM/DD): 20____/____/____	
AA1:	AA2:	AA3:	Village:
HH ethnic group (optional):	HH type (optional):	HH code:	Consent: _____
Respondent's Age:____ **Gender:** *M (1) | F(2)*	**Head of HH's Age:**____ **Gender:** *M(1) | F(2) | M&F(3)*		
Head of HH's Marital Status: *married(1) | single(2) | divorced(3) | widowed(4)*			

1 Can the head of the household read a newspaper?

No (1)	Yes, with difficulty (2)	Yes, without difficulty (3)	Don't know (4)

2 During the last 12 months, how many adults (age 15 and older) lived and slept in your home for 9 or more months?

Female adults		Male adults		Don't know (-1)

3 During the last 12 months, how many adults lived and worked **outside** your home for 3 or more months?

Adults	

4 During the last 12 months, how many children (age 14 and younger) lived and slept in your home for 9 or more months?

Females <5		Males <5		Females 5-14		Males 5-14	
Household has no children (-1) *[skip to question 9]*							

5 *[If there are no school-age children (age 5-14) in the household skip to question 7]*
During most of the year, how long does it take, in minutes, for the school-age children (age 5-14) in your household to go to school (one-way, by any means: for example, walking, bicycle, scooter, bus)?

# of minutes =		*[If children attend more than one school, enumerator to record the average time]*	Children usually live at school (-1)
School-aged children do not regularly attend school (-2)			Don't know (-3)

6 Can your household afford your children's school fees and school supplies?

No (1)	Rarely (2)	Sometimes (3)	Usually (4)
Yes (5)	Household does not pay the fees and cannot afford supplies (6)		
Household does not pay fees, but can afford supplies (7)		Household does not pay fees or supply costs (8)	

7 What is the highest level of schooling the female children in your household will **likely** complete?

No female children (-1)	Don't know (-2)
Highest likely level =	

8 What is the highest level of schooling the male children in your household will **likely** complete?

No male children (-1)	Don't know (-2)
Highest likely level =	

1. No formal education
2. Primary school (age 5 or 6 until age 11 or 12)
3. Junior school (age 11 or 12 until age 14 or 15)
4. High school (age 14 or 15 until age 18 or 19)
5. Technical or vocational school (post Junior school or High school, usually 2 years)
6. College or university (post high school, 3 to 5 years)
7. Advanced degree (Masters, MBA, PhD, etc.)

9 In the last 12 months, how often have members of your household had a non-serious illness (meaning they were sick, but not so sick they had to rest in bed all day)?

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

10 In the last 12 months, how often have members of your household been seriously ill (meaning they were so ill that they stay in bed, or lying down, for two or more days)?

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

11 How much time does it take for members of your household to reach the nearest health center which can diagnosis simple illness, or treat simple injuries, and prescribe basic medicines?

Household self-diagnoses, self-medicates for simple illnesses (-1)		
No health center in the area or center is too far to travel to (-2) *[skip to question 14]*	Minutes =	

12 How often does this health center have enough medical supplies to provide adequate healthcare?

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

13	How much time does it take for members of your household to reach the nearest health center which can diagnosis and treat complicated or serious illnesses or injuries (can perform surgery)? No health center for serious illness, or center too far to reach easily (-1) / Don't know (-2) / Minutes =
14	Can your household afford professional treatment for serious illness or injury? No (1) / Yes, if money is borrowed (2) / Yes, with much difficulty (3) / Yes, with some difficulty (4) Yes, because government or employer helps pay for treatment (5) / Yes, household can afford it (6)
15	For the majority of the households in your village/area, do you think there is a better chance for women or men to receive healthcare when needed? Women (1) / Men (2) / About the same (3) / Don't know (4)
16	Are the healthcare centers in your village/area (within two hours distance from your home) **usually** able to provide women with adequate healthcare **if** they seek it? There are no healthcare centers in our village-area (1) / No (2) / Rarely (3) / Sometimes (4) Often (5) / Always (6) / Yes, but women prefer not to go (for whatever reason) (7) / Don't know (8)
17	*[Information to be collected by enumerator while in the household (ask only if unable to determine answer visually)]* What is the **primary** construction material of the housing unit's exterior walls? Reinforced concrete (1) / Stone & mortar (2) / Cement blocks (3) / Brick (fired/burned) (4) Metal sheeting (5) / Logs or thick wood (6) / Thin wood (7) / Bamboo (8) Brick (mud or earth) (9) / Mud & straw (10) / Earth or adobe (11) / Reeds/thatch (12) Thick plastic (13) / Fabric or thin plastic (14) / Other, specify (15):
18	*[Information to be collected by enumerator while in the household (ask only if unable to determine answer visually)]* What is the **primary** construction material of the housing unit's main roof? Roofing shingles (1) / Ceramic tiles (2) / Synthetic roofing (3) / Metal sheeting (4) Cement or concrete (5) / Thin wood (6) / Thick wood (7) / Bamboo (8) Thick plastic (9) / Thin plastic or fabric (10) / Straw or reeds (11) / Other, specify (12):
19	Can your home withstand strong winds, severe rain, snow or hail without significant damage? No (1) / Yes (2) / Yes, with minor damage (3) / Perhaps, but with significant damage likely (4) Little to no extreme weather in this region (5) / Don't know (6)
20	What is the **primary** source of light your home uses when it is dark?
21	What is the **primary** fuel source your household uses for cooking?
22	What is the **primary** fuel source your household uses for heat?

1. None	8. Liquid fuel [petrol, kerosene]
2. Heat not needed in region	9. Coal or charcoal
3. High-voltage electricity from grid [legal or illegal connection]	10. Vegetable or animal based fats or oils
4. Low-voltage electricity from grid [legal or illegal connection]	11. Candle, paraffin wax, or battery-powered source
5. Electricity from a generator	12. Wood, sawdust, grass or other natural material
6. Electricity from solar cells, wind turbine or small dam	13. Don't know
7. Gas fuel [from tank or biogas]	14. Other, specify:

23 What type of toilet facility does your household usually use?

None, open defecation (1) *[skip to question 25]*	
Open pit, communal (2)	Open pit, private (8)
Enclosed pit, communal (3)	Enclosed pit, private (9)
Enclosed improved-ventilation pit, communal (4)	Enclosed improved-ventilation pit, private (10)
Enclosed pour-flush, communal (5)	Enclosed pour-flush toilet, private (11)
Enclosed flush, communal (6)	Enclosed flush, private (12)
Compost or biogas, communal (7)	Compost or biogas, private (13)
Other, specify (14):	
"Open" means there is no structure, or a structure with no roof. "Enclosed" means there is a structure with any sort of roof. "Communal" means the facility is shared by 3 or more households. "Private" means the facility is used by 1-2 households.	

24 *[If the household uses a toilet facility of any kind, ask:]* Over the last 12 months, how often was the toilet **usable**? (meaning it was working properly or was available to use)

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

25	What does your household usually do with food waste/remains (any parts not consumed by people in the household)?	
26	What does your household usually do with non food waste/garbage?	
27	What does your household usually do with wastewater (for example, from bathing, cleaning, the toilet)?	

[Enumerator to remind respondent "all responses are anonymous"]

1. Discard close to a house [within 25 meters]	
2. Discard near a house [25 to 75 meters from the house]	
3. Discard far from a house [75 meters or more]	
4. Feed to livestock	10. Burn it
5. Feed to pets or guard dogs	11. Compost it
6. Use for biogas generation	12. Sell to vender
7. It is collected regularly within 75 meters of a house [organized garbage collection]	13. It is collected regularly further than 75 meters from house [organized garbage collection]
8. Put down the drain [piped sewage network]	14. Use to water crops grown for livestock fodder
9. Use to water vegetable garden	15. Discard into local waterway or irrigation canal
16. Discard into septic tank	17. Other, specify:

28 How many times a week do most members (the majority) of your household clean their teeth?

Never (1)	Rarely (2)	One or two days a week (3)	Most days of the week (4)
Usually once a day (5)	Usually two or three times a day (6)		Don't know (7)

29 How often do the adults in your household clean their hands before eating a meal?

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

30 How often do the adults in your household clean their hands after defecating?

Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Don't know (6)

31 Do the adults in your household use soap (any kind of soap) when they clean their hands?

No (1)	Yes, but very rarely (2)	Yes, but only when guests visit (3)	Yes, after defecating (4)
Yes, before meals (5)	Yes, after defecating and before meals (6)	Don't know (7)	Other, specify (8):

32 What is the **primary source** (meaning, the source water comes from immediately before being used) of the water your household uses for drinking and cooking inside the home?
[If the household uses different water sources for drinking and cooking, only record the drinking water source]

During the rainy season	During the dry season	During most of the year
No rainy season in our area (-1)	No dry season in our area (-2)	Don't know (-3)

1. Piped from water treatment plant (chlorinated)	13. Water vender with tanker truck
2. Piped from water treatment plant (not chlorinated)	14. Water vender with cart or small tank
3. Borehole (> 20m deep)	15. Large dam (built & managed by government, company or collective)
4. Borehole (< 20m deep)	
5. Private well (> 20m deep)	16. Small dam (built & managed by households, village or collective)
6. Private well (< 20m deep)	17. Stream
7. Communal well (> 20m deep)	18. River
8. Communal well (< 20m deep)	19. Pond, lake (or other still water body)
9. Protected ("box") spring	20. Irrigation canal
10. Unprotected spring	21. Bottled water (delivered by vender)
11. Rainwater harvesting container (closed)	22. Bottled water (collected by household)
12. Rainwater harvesting container (open)	23. Other (specify):

["Private" means used primarily by the household, but may also be shared with 2-4 other households, and is located within 100 meters of the household. "Communal" means it is shared by 5 or more households.]

33 Approximately how much time (in minutes) does it take your household to collect enough water for your household's drinking and cooking needs for a normal (average) day?
[Total time = there and back for each person and trip combined.
If water is collected from inside the household or in the household's yard/compound, write "1" minute]

During the rainy season	During the dry season	During most of the year
No rainy season in our area (-1)	No dry season in our area (-2)	Don't know (-3)

34 Does your household treat water before drinking it (any treatment method: boiling, allowing to settle, filter, chemical treatment, etc.)?

No treatment is necessary (1)	Never (2)	Rarely (3)	Sometimes (4)	Often (5)	Always (6)

35	During the last 12 months, for how many months was your household's main source of water sufficient to meet your household's drinking and cooking needs? Months: [ ] | Don't remember (-1)
36	How often do you worry there will not be enough water from your household's main water source to satisfy your household's drinking and cooking needs? Never (1) | Rarely (2) | Sometimes (3) | Often (4) | Always (5)
37	Can your household usually afford to pay the fees (direct payments only, not maintenance fees) for using water from your household's main water source? No (1) | Rarely (2) | Sometimes (3) | Often (4) | Always (5) | They do not need to pay for water (6)
38	Generally, what do you think the quality of your households' drinking water is (before any treatment)? Don't know (1) | Very bad (2) | Poor (3) | Satisfactory (4) | Good (5) | Very good (6)
39	Does your household have access to land for agriculture, orchards, livestock or aquaculture (meaning fish-farming)? Yes, have access and using the land (1) | Yes, have access and leasing some land to others (2) No access to land because leasing to others (3) *[skip to question 51]* | No access to land (4) *[skip to question 52]*
40	How much land does your household have for agriculture (for crops, grasses, trees, orchards, etc.)? Mu (亩): [ ] | Don't know (-1) | None, only access for livestock/aquaculture (-2) *[skip to question 46]*
43	During the last two years, was your household able to make, or buy, enough compost/manure or artificial fertilizer for each growing season? Household does not think they need to use compost/manure or fertilizer (1) No (2) | Rarely (3) | Sometimes (4) | Often (5) | Always (6)
44	During the last two years, was your household able to afford enough seeds for each growing season? Not necessary because household saved seeds (1) | No (2) | Rarely (3) | Sometimes (4) Often (5) | Always (6) | Other, specify (7):
45	Is there generally enough water for your household's crops during the dry season/rest of the year? Dry season [ ] Rest of the year [ ] Never (1) | Rarely (2) | Sometimes (3) | Often (4) Always (5) | No dry season in our area (6) | Few, or no, crops grown (7)
46	Is there generally enough water for your household's livestock during the dry season/rest of the year? Dry season [ ] Rest of the year [ ] Little, or no, livestock (1) *[skip to question 48]* | Never (2) | Rarely (3) Sometimes (4) | Often (5) | Always (6) | No dry season in our area (7)
47	During the last two years, how often was your household able to grow, collect or buy enough fodder? Never (1) | Rarely (2) | Sometimes (3) | Often (4) | Always (5)
48	Is there generally enough water for your household's aquaculture during the dry season/rest of the year? Dry season [ ] Rest of the year [ ] Little, or no, aquaculture (1) *[skip to question 50]* | Never (2) | Rarely (3) Sometimes (4) | Often (5) | Always (6) | No dry season in our area (7)
49	During the last two years, how often was your household able to make or buy enough fish feed? Never (1) | Rarely (2) | Sometimes (3) | Often (4) | Always (5)
50	Does your household usually have enough people to work/manage your farm? (crops, orchards, forestry, livestock, and/or aquaculture) Never (1) | Rarely (2) | Sometimes (3) | Often (4) | Always (5)
52	Of all the **possible negative events** (natural or socioeconomic) which **could** occur in the next 12 months, and which would have a bad or damaging impact on your household, which three are you most worried about? (as far as negative impacts to household members, livelihoods, agriculture, livestock, aquaculture…) *[Enumerator to write down up to three events in the spaces provided, from most worried about (52.1) to less worried about (52.3)]*
53	For these events, **how damaging** would each be for your household? *["likely severity"]*
54	For these events, **how likely** is it that the event will occur in the next 12 months? *["likely frequency"]*

Don't know (-1) *[skip to question 59]*	Not very worried about any negative events (-2) *[skip to question 59]*		
Likely severity=	Low-minor (1)	Middle-moderate (2)	High-major (3)
Likely frequency=	Unlikely (1)	Likely (2)	Very likely (3)

1st	52.1)	write in	53.1) Likely severity=		54.1) Likely frequency=	
2nd	52.2)	write in	53.2) Likely severity=		54.2) Likely frequency=	

3rd	52.3)	write in	53.3) Likely severity=	54.3) Likely frequency=	

55 If the worst of the negative events you just mentioned *[in question 52]* were to occur in the next 12 months, what are the three main ways your household would likely react (cope)?

Don't know (-1)	Primary strategy		Secondary strategy		Tertiary strategy	

1. Seek off-farm work	10. Children help more than usual with household work	19.Sell stored grain	28.Postpone payment of debts
2. Work more hours or take on other jobs	11. Ask friends to help with farm labor or business	20.Sell livestock	29.Borrow money from relatives
3. Start a business	12. Ask family to help with farm labor or business	21.Use savings or sell jewelry	30.Borrow money from friends
4.Reduce healthcare spending	13.Rely on local government	22.Sell durable goods	31.Borrow money from cooperative or village fund (community source)
5.Reduce alcohol consumption	14.Rely on national government	23.Sell farmland	32.Borrow money from bank or other financial service provider
6.Reduce meat consumption	15.Rely on aid orga izat ons	24.Sell business	33. Borrow money from private lender
7.Re uce fuel c nsumption	16.Rely on group insurance	25.Sell/leave home (live with relatives in area)	34.Send children to work outside the household
8.Plant fewer crops next growing season	17.Rely on private insurance	26.Sell/leave home (move to another area)	35.Take children out of school so they can work
9.Lease out farmland	18.Seek technical assistance	27. Seek medical treatment	36.Beg for money/food
37. Other, specify:			

56 If the worst of the negative events you just mentioned *[in question 52]* were to occur in the next 12 months, how long do you think it would take for your household to return to a satisfactory situation? *[Record answer in months (for example, 2 years = 24 months)]*

Don't know (-1)	Less than one month (-2)	Months=		Our household could not recover (-3)

57 If in an extreme disaster (of any sort) your household's home was completely destroyed, but your family members were not injured, how long would it take for your household to rebuild your home?

Don't know (-1)	We would move (-2)	Months =		Our household could not rebuild (-3)

58 If the worst of the negative events you just mentioned *[in question 52]* were to occur in the next 12 months, who do you think would be most likely to assist your household?

No one (1)	Family/relatives (2)	Friends (3)	Insurance company (4)
Financial institution (5)	Local government (6)	National govt. (7)	Government (general) (8)
Aid organizations (9)	Don't know (10)	Other, specify (11):	

59 During the last 12 months, did any member of your household eat fewer meals, or smaller portions, than usual because there was not enough food? *[If "yes", for approximately how long?]*

Never (1)	Yes, once or twice (2)	Yes, for about one week (3)	Yes, for a few weeks (4)
Yes, for about one month (5)	Yes, for more than one month (6)	Yes, most days (7)	Don't know (8)

61 During the past 12 months, did your household experience a period of time longer than two weeks when there was not enough food? *[if "yes", how many such periods?]*

No (1)	Yes, one (2)	Yes, two (3)	Yes, three (4)
Yes, four (5)	Yes, more than four (6)	Don't remember (7)	Other, specify: (8)

62 During the past 12 months, did your household ever experience one full day with no food to eat? *[If "yes", how often did this occur?]*

Never (1)	Once or twice (2)	Approximately once a month (3)
Approximately every two weeks (4)	Approximately every week (5)	Don't know (6)

63 During the last 12 months, how often did the majority of your household eat the following foods?

.1	Grains (cereals, bread, rice, pasta)		1. Never
.2	Roots &/or tubers (potatoes)		2. Almost never
.3	Vegetables/greens		3. Approximately once a month
.4	Fruits		4. A few times a month
.5	Dairy &/or eggs		5. About once a week
.6	Meat &/or fish-seafood		6. A few times a week
.7	Nuts &/or legumes (and/or derivatives, tofu, etc.)		7. Every day
			8. Not eaten for religious or cultural reasons

71	Does your household have a television? *[If none write "0"]* Number of televisions ☐
74	On most days, what type of water does your household (most members of the household) drink? Large Tong or small bottles (1) | Boiled water (2) (source is tap water) ***[skip to question 79]*** | Boiled water (3) (source is <u>not</u> tap water) ***[skip to question 79]*** | Raw (non-boiled) water (4) ***[skip to question 84]*** | Other, specify (5): ***[skip to question 84]***
75	How many liters are in each Tong (or bottle)? Don't know (-1) | One tong (bottle) = liter ☐
76	How much does one Tong (or bottle) cost? Don't know (-1) | RMB = ☐
77	Does someone from your household go to collect the Tong (bottle) or is it delivered to your home? Household collects the Tong/bottle (1) | Tong/bottle is delivered (2) | Other, specify (3):
78	Why does your household choose to drink Tong/bottled water? ***[Skip to question 86]*** The tap water is poor quality (1) | We do not have tap water (2) | Bottled water is affordable (3) Bottled water is safe (4) | Bottled water tastes good (5) | It is convenient (6) Because lots of people drink Tong/bottled water (7) | Other, specify (8):
79	What is the primary fuel source your household uses for boiling drinking water? Dry season (winter) ☐ Rest of the year (summer) ☐ 1. None | 2. Stable voltage electricity from grid [legal or illegal connection] 3. Unstable voltage electricity from grid [legal or illegal connection] 4. Electricity from a generator | 5. Electricity from solar cells, wind turbine or small hydroelectric dam 6. Biogas | 7. Liquid Petroleum Gas (LPG) | 8. Natural gas | 9. Kerosene 10. Honeycomb coal (briquette) | 11. Coal/coke/lignite 12. Charcoal | 13. Dung cakes (animal feces) 14. Vegetable or animal based fats/oils | 15. Candle, paraffin wax, or battery-powered source | 16. Wood (logs) 17. Wood (twigs/branches) | 18. Crop residue | 19. Don't know
80	What is the main reason that you use this type of fuel? *[If "convenient", please specify why it's convenient]* Fuel is available when needed (1) | Fuel available near my home (2) | Easy to carry (3) Low cost of the stove (4) | Low cost of the fuel (5) | Easy to use when cooking (6) Fuel can be purchased in small amounts which we can afford (7) | Electricity is convenient(8) Other, specify (9):
81	When your household boils water for drinking (or tea), how much time do you usually use? Don't know (-1) | Often too busy to heat water (-2) | Minutes for electric kettle = ☐ Water kettle is often left on the stove top, so the water is always warm (-3) | Minutes for fuel source other than electric kettle = ☐
82	Approximately how many times does your household heat water each day? Dry season (winter) ☐ Rest of the year (summer) ☐
83	When your household boils [heats] water, do you heat the water until it is warm, until it is very warm, until it is boiling, or until it is boiling for a short time? Warm (1) | Very warm (2) | Boiling (3) | Boiling for a period of time (4) | Don't know (5)
84	How does your household normally treat your drinking water? Heat water to a boil (1) | Don't usually treat water (2) ***[skip to question 86]*** Heat water, but not to a boil (3) | First let water stand so sediment can settle, then heat (4) Filter/straining with a cloth (5) | Let water stand so sediment can settle (6) Liquid bleach (7) | Bleach powder (8) Liquid chlorine (9) | Solar disinfection (10) Ceramic filter (11) | Biosand filter (12) Membrane filter (13) | Water purification machine (14) Other, specify (15):

85 Generally, who in your household is responsible for treating the household's drinking water?

1. Female/s under 5	2. Female/s aged 5-14	3. Female/s aged 15 or older	4. Male/s under 5	5. Male/s aged 5-14	6. Male/s aged 15 or older
7. (1) & (2)	8. (2) & (3)	9. (4) & (5)	10. (5) & (6)	11. (3) & (6)	12. Not fixed
13. Don't know		14. Other (specify):			

86 How many of your relatives in your village/area drink boiled water?

Don't know (1)	None (2)	Some (3)	About half (4)	Most (5)	All (6)

87 How many of the households in your village/area drink boiled water?

Don't know (1)	None (2)	Some (3)	About half (4)	Most (5)	All (6)

88 How does your household usually store your drinking water (boiled or non-boiled)? *[and is it usually covered or uncovered?]*

Household drinks straight from tap (1)	Store water in small plastic bottle/s (2)
[19L] Tong/bottled water, without base/spigot (3)	[19L] Tong/bottled water, with base/spigot (4)
Store water in an uncovered clay pot (5)	Store water in a clay pot, and then cover it (6)
Store water in an uncovered metal pot (7) [specify the specific metal:_____________]	Store water in a metal pot, and then cover it (8) [specify the specific metal:_____________]
Store in a glass container (9)	Store in a vacuum flask/thermos (10)
Store water in a covered plastic container (jerry can, bucket or other) (11)	Store water in an uncovered plastic container (jerry can, bucket or other) (12)
Store water in covered container with spigot/tap (13)	Store water in uncovered container with spigot/tap (14)
Do not store water (purchase small plastic bottle and drink water directly) (15)	Other, specify (16):

89 How often do members of your household (older than 15) drink untreated water?

Never (1) **[skip to question 91]**	Rarely (2)	Sometimes (3)	Often (4)	Always (5)

90 When do members of your household (older than 15) drink untreated water?

Never (1)	When there is no boiled water (2)	When working in the field (3)	When working (non-farm work) (4)	When in school (5)	Other, specify (6):

91 How often do children in your household (0~14 years old) drink untreated water?

No children (1) **[skip to question 93]**	Never (2) **[skip to question 93]**	Rarely (3)	Sometimes (4)	Often (5)	Always (6)

92 When do children in your household (0~14 years old) drink untreated water?

Never (1)	When there is no boiled water (2)	When working in the field (3)	When playing (4)	When in school (5)	Other, specify (6):

93 If people drink untreated water, what do you think will happen to them? *[Select their first answer only]*

Nothing (1)	Nothing, if it is rainwater (2)
Nothing, if it is spring water (3)	Nothing, if it is from a borehole (4)
They will get sick (5)	They will get diarrhea (6)
They will vomit (7)	They will get a stomach ache (8)
They will get typhoid (9)	They will get cholera (10)
They will get amoeba (11)	Other, specify (12):

94 If you drink untreated water, could you then easily get diarrhea?

Don't know (1)	No, won't get it (2)	Maybe, but not easily (3)	Yes, it's easy (4)

95 If you get diarrhea, how severe would the impact on your life be?

Don't know (1)	Very little impact (2)	Moderately severe (3)	Very severe (4)

96 What is the best way to make water safer for drinking?

Heat water to a boil (1)	Don't know any ways to make water safe (2)
Heat water, but not to a boil (3)	First let water stand so sediment can settle, then heat (4)
Filter/straining with a cloth (5)	Let water stand so sediment can settle (6)
Liquid bleach (7)	Bleach powder (8)
Liquid chlorine (9)	Solar disinfection (10)
Ceramic filter (11)	Biosand filter (12)
Membrane filter (13)	Water purification machine (14)
Tong/bottled water (15)	Other, specify (16):

97	What is the reason your household treats or boils water before drinking it? *[Select their first answer only]* Household does not treat water (1) | Water is not safe, but don't know the reason (2) | To avoid disease (3) To avoid stomach problems (4) | To remove germs (5) | To kill germs (6) Rainwater does not need to be treated (7) | Remove/eliminate foreign substances (8) | Other, specify (9):	
98	*[If the household does not drink Tong/bottled water, ask:]* What do you think about your household's drinking water quality? *[If they think it is poor quality ask why?]* We think our water quality is fine (1) | The water is contaminated with fecal matter from people (2) The water is naturally low quality (3) | The water is contaminated with fecal matter from animals (4) The area near the water source is dirty (5) | The water is contaminated with fecal matter from people and animals (6) People clean clothing in the water (7) | The water is contaminated with chemicals from factories (8) The water is contaminated with chemicals from agriculture (9) | The water treatment plant does not treat the water well enough (10) Don't know what the water quality is (11) | Other, specify (12):	
99	Which tastes best to you: untreated water, boiled water, Tong/bottled water, or treated water (any method except boiling)? Don't know (1) | Untreated (2) | Boiled (3) | Tong/Bottled (4) | Treated water (5) | Other, specify (6):	
100	Would you be willing to buy a high-quality filter to filter your drinking water? (filter which allows you to directly drink the water). If you are willing, what is the most money you would be willing to spend? Don't know (1) | I would not spend any money because it's not important enough (2) I would not spend any money because I don't want to spend money (3) | 100-300 RMB (4) | 300-500 RMB (5) | 500-1000 RMB (6) | More than 1000 RMB (7) Our household already purchased a water filter, the price was (8): RMB =	
101	In your household, where does cooking take place on most days: inside or outside or both? Dry season [ ] | Rest of the year [ ] Inside (1) | Outside [meaning an area with no roof] (2) | Inside & outside (3) | Other, specify (4):	
102	Where does your household heat water for drinking on most days? Dry season [ ] | Rest of the year [ ] Inside (1) | Outside (2) | Inside & outside (3) | Household does not regularly boil water for drinking (4) | Other, specify (5):	
103	Did you have diarrhea in the last two weeks? If so, how many times? Diarrhea (times) [ ]	
104	*[If the household does not drink Tong/bottled water, ask:]* Why doesn't your household drink Tong/bottled water? Too expensive (1) | Not easy to get it (2) | Not safe (3) | I don't know (4) | Other, specify (5):	
105	*[If the households does not drink boiled water,* ***skip to question 107****]* Is the cooking space in a different (separate) place from where people in the household usually stay? No, not separate (1) | Yes, the cooking space is in a separate structure/building (2) | Yes, the cooking space is separated by a doorway with a door or flap/fabric (3) | Yes, the cooking space is separated by a doorway, but no door/flap (4) | Other, specify (5):	
106	*[Without asking the respondent, enumerator to observe and record how the cooking area is ventilated]* Ventilation from opening in wall or ceiling only (1) | Ventilation from windows only (2) | Ventilation from doorway to outdoors only (3) | Ventilation from windows and doorway to outdoors (4) Fuel is burned in a stove with a pipe/chimney which vents inside the home (5) | Fuel is burned in a stove with a pipe/chimney which vents to the outside (6) | Other, specify (7):	
107	*[Enumerator to ask respondent to please see the hand-washing area to check if soap is available]* Yes, there is soap which appears to be used regularly (1) | There is soap, but it does not appear to be regularly used (2) | There is no soap (3) | Respondent did not wish to allow enumerator to see hand-washing area (4)	

Additional survey questions completion time: _____:_____

附件 1　　入户调查表

调查员： ______________	时间 _____:_____ 到 _____:_____	日期（年/月/日）：20____/____/____

县（AA1）：	乡镇（AA2）：	村（AA3）：	队名：
家庭少数民族类别　（可选）：	家庭类型（ 可选）：	家庭编码：	同意：_____

应答人年龄：_____　性别：*男 (1) | 女 (2)*　　**家主年龄：**_____　性别：男 *(1) |女 ((2) | 男和女 (3)*

家主婚姻状况：已婚 *(1) | 单身(2) | 离异(3) | 寡居(4)*

1 家主会看报纸吗？

不会 (1)	会，但有困难 (2)	会，没困难 (3)	不知道 (4)

2 在过去 12 个月内，有多少成年人（15 岁或以上）在家居住 9 个月以上？

女性成年		男性成年		不知道 (-1)

3 在过去 12 个月内，有多少成年人在家庭外居住或工作 3 个月以上？

成年人	

4 在过去 12 个月内，多少儿童（14 岁或以下）在家居住 9 个月以上？

女 <5 岁		男 <5 岁		女 5-14 岁		男 5-14 岁	
家里没小孩 (-1) *[跳到问题 9]*							

5 *[如果家里没有学龄儿童（5-14 岁），跳到问题 7]*

一年中大部分时间，您家里的学龄儿童需要多长时间（以分钟计算）去上学（单程，任何方式：例如步行、自行车、踏板车、公交车）？

分钟数 =		*[如果儿童去 1 个以上学校上学，调查员需记录平均时间.]*	儿童通常住校 (-1)
学龄儿童没有定期上学(-2)			不知道 (-3)

6 您家里能负担儿童上学费用和物资吗？

不能 (1)	很少 (2)	有时 (3)	通常 (4)
能 (5)	家庭不能付费，也不能承担物资供给 (6)		
家庭不能付费，但能承担物资供给 (7)		家庭不必支付费用和物资供给成本(8)	

7 在您家里，女孩(0-14 岁)**可能**接受教育的最高程度是什么？

没有女孩 (-1)	不知道 (-2)
最高可能程度 =	

8 在您家里，男孩(0-14 岁)**可能**接受教育的最高程度是什么？

没有男孩 (-1)	不知道 (-2)
最高可能程度 1 =	

1. 没有正规教育
2. 小学 (5、6 岁到 11 、 12 岁)
3. 初中 (11、 12 岁到 14 、 15 岁)
4. 高中 (14、 15 岁到 18、 19 岁)
5. 技术或职业学校 (初中或高中后，通常 2 年)
6. 学院或大学 (高中后， 3 到 5 年)
7. 更高等学位（硕士、 MBA、 PhD 等）

9 在过去 12 个月内，您家里人是否经常患不严重的疾病（指他们患病了，但没有严重到需要整天卧床休息）？

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	不知道 (6)

10 在过去 12 个月内，您家人是否经常患严重的疾病？（指他们病重到必须滞留或躺在床上 2 天或 2 天以上）

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	不知道 (6)

11 您家人需要多长时间到达最近的村卫生所？（能诊断一般疾病、处理小伤害和开具基本药物）

家庭简单疾病的自我诊断和自我治疗 (-1)

<table>
<tr><td></td><td>家庭附近没有卫生院或卫生院太远去不了(-2) [跳到问题 14]</td><td>分钟数 =</td><td></td></tr>
<tr><td>12</td><td colspan="3">该卫生所平常是否能提供足够的医疗保健服务？
从来没有(1) | 很少 (2) | 有时 (3) | 经常 (4) | 总是 (5) | 不知道 (6)</td></tr>
<tr><td>13</td><td colspan="3">您家人需要多长时间到达最近的卫生院？（能诊断和处理复杂或严重疾病或伤害（能进行外科手术））
没有处置严重疾病的卫生院，或卫生院太远不易到达 (-1) | 不知道 (-2) | 分钟数 =</td></tr>
<tr><td>14</td><td colspan="3">您家庭能负担严重疾病或伤害的治疗费用吗？
不能(1) | 能，如果是 借钱 (2) | 能，但很困难 (3) | 能，有一些困难 (4)
能，因为政府或顾主负担治疗费 (5) | 能，家里能负担 (6)</td></tr>
<tr><td>15</td><td colspan="3">对于您村里或附近地区大部分家庭来说，男性或女性具有同等接受医疗保健的机会吗？
女性多(1) | 男性多(2) | 基本一样 (3) | 不知道 (4)</td></tr>
<tr><td>16</td><td colspan="3">您村或附近的医疗机构（离您家 2 小时路程）通常能够为妇女提供充分的保健服务吗？
村里或周边没有 卫生院 (1) | 从不(2) | 很少 (3) | 有时 (4)
经常 (5) | 总是 (6) | 能，但妇女更倾向 于不去 (无论什么原因)(7) | 不知道 (8)</td></tr>
<tr><td>17</td><td colspan="3">[信息应由调查员在入户调查时收集(仅在不能通过观察确定答案时提问)]
家庭外墙的主要建筑材料是什么？
强化混凝土 (1) | 石头和灰浆 (2) | 水泥块 (3) | 砖 (烧制/煅烧) (4)
金属片 (5) | 原木或粗木 (6) | 细木 (7) | 竹子 (8)
砖 (泥或土) (9) | 泥和稻草 (10) | 泥土和土坯砖(11) | 芦苇/茅草 (12)
厚塑料 (13) | 织物或薄塑料 (14) | 其它，详细说明 (15):</td></tr>
<tr><td>18</td><td colspan="3">[信息应由调查员在入户调查时收集(仅在不能通过观察确定答案时提问)]
家庭主要屋顶/天花板的主要建筑材料是什么？
屋顶保护板 (1) | 瓷砖 (2) | 屋顶合成材料(3) | 金属片 (4)
水泥或混凝土 (5) | 细木 (6) | 粗木 (7) | 竹子 (8)
厚塑料 (9) | 织物或薄塑 (10) | 稻草或芦苇 (11) | 其它，详细说明(12):</td></tr>
<tr><td>19</td><td colspan="3">你家能经受住强风、暴雨、暴雪或冰雹，且不会出现严重损害吗？
不能(1) | 能(2) | 能，但有小损坏 (3) | 也许，但可能会出现严重损坏 (4)
该地区少有或没有极端天气(5) | 不知道 (6)</td></tr>
<tr><td>20</td><td>天黑时，你家里使用的主要光源是什么？</td><td></td><td rowspan="3">1. 没有 | 8. 液体燃料 [汽油、煤油]
2. 该地区不需取暖 | 9. 煤或木炭
3. 从电网来的高压电[合法或非法连接] | 10. 植物或动物脂肪或燃油
4. 从电网来的低压电[合法或非法连接] | 11. 蜡烛、石蜡或电池驱动
5. 发电机电流 | 12. 木头、锯末、草或其它天然原料
6. 太阳能电池、风轮或小水库来的电力 | 13. 不知道
7.煤气 [来自气罐或沼气池] | 14. 其它，详细说明：</td></tr>
<tr><td>21</td><td>你家里做饭使用的主要燃料是什么？</td><td></td></tr>
<tr><td>22</td><td>你家里取暖使用的主要燃料是什么？</td><td></td></tr>
</table>

23 你家里通常使用什么样的厕所设施？

没有，随地大小便 (1) ***[跳到问题 25]***	
敞口坑，公用 (2)	敞口坑，私用 (8)
封口坑，公用 (3)	封口坑，私用(9)
密封通风改良厕所，公用 (4)	密封通风改良厕所，私用 10)
封闭下水道水冲式，公用 (5)	封闭下水道水冲式，私用 (11)
封闭水冲式，公用 (6)	封闭水冲式，私用 (12)
堆肥或沼气，公用 (7)	堆肥或沼气，私用 (13)
其它，详细说明 (14)：	
“敞口”是指没有建筑物，或建筑物没屋顶。 “封闭” 是指有任何形式屋顶的建筑物。 “公用” 是指设施由 3 家或更多家庭共同使用。“私用”是指设施由 1-2 家使用。	

24 *[如果某个家庭使用任何形式的厕所设施，请问：]* 在过去 12 个月内，厕所经常使用吗？ (是指正常运行或能够被使用)

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	不知道 (6)

[调查员：“所以回答都是匿名的”]

25 你家通常怎样处理食物残渣/和废弃物（任何没有消费的部分）？

26 你家里怎样处理非食物残渣/垃圾？

27 你家里通常怎样处理污水（如洗澡、清洗、厕所）？

1． 丢弃到房子旁边 [离房子 25 米内]	
2． 丢弃到房子附近 [离房子 25 到 75 米]	
3． 丢弃到远离房子的地方 [离房子 75 米和更远]	
4． 喂家畜	10． 烧掉
5． 喂宠物或看门狗	11． 堆肥
6． 用于产生沼气	12． 卖给叫卖商
7． 离家 75 米内定期收集[统一垃圾收集]	13． 家庭 75 米外 定期收集[统一垃圾收集]
8． 倒如下水道 [管网污水系统]	14．用于浇灌作为家畜饲料的作物
9． 用于浇灌菜园	15． 排入开放的污水沟
16. 自己挖坑作化粪池，自然渗透和蒸发	17． 其它，详细说明：

28 你家大多数人每人一周刷牙几次？

从不 (1)	很少 (2)	一周 1、2 次 (3)	每周大部分日子 (4)
通常每天一次 (5)	通常一天 2、3 次 (6)		不知道 (7)

29 你家成人平常饭前洗手吗？

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	不知道 (6)

30 你家成人平常便后洗手吗?

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	不知道 (6)

31 你家成人洗手时用肥皂（任何种类）吗?

从不 (1)	是，但很少 (2)	是，只在有客来访时 (3)	是，便后 (4)
是，饭前 (5)	是，饭前和便后 (6)	不知道 (7)	其它，详细说明 (8)：

32 你家里饮用和准备 食物时的主要水源（指使用前来自哪里的水源）？（如果饮用和食物的水源不一样，调查饮用水的水源）

在雨季	在旱季	一年大部分时间
地区无雨季(-1)	地区无旱季 (-2)	不知道(-3)

2.管网 (来自水库，未处理)	14. 使用推车或小水箱的卖水商
3. 钻井 (> 20m 深度)	15. 大型水库（政府、公司或集体建造和管理的）
4. 钻井 (< 20m 深度)	
5. 私有井 (> 20m 深度)	16. 小水库 (家庭、村庄或集体建造和管理)
6. 私有井 (< 20m 深度)	17. 溪流
7. 公用井 (> 20m 深度)	18. 河
8. 公用井 (< 20m 深度)	19. 池、湖 (或其它静水体)
9. 受保护的("圈起来")泉水	20. 灌溉渠
10. 未保护的泉水	21. 瓶装水 (水商运送)
11. 雨水收集器 (密封)	22. 瓶装水 (家庭收集)
12. 雨水收集器 (未密封)	23. 其它（详细说明）:

["私用"是指 主要由家庭使用，但也可能与 2-4 家其它家庭共用，位置处于家庭 100 米之内。 "公用"是 指由 5 个或 5 个以上家庭共用.]

33 平均一天正常饮用和做饭用水，需要大约多长时间取水(分钟数)?

[总时间 = 每个来回一个人需要的时间与次数乘积如果是在家里或庭院/院子取水， 填写"1"分钟]

在雨季		在旱季		一年大部分时间	
地区无雨季(-1)		地区无旱季 (-2)		不知道(-3)	

34 你家在饮水前处理水吗 (任何处理方法：烧开、沉淀、过滤、化学处理等)?

不需要处理 (1)	从未处理 (2)	很少 (3)	有时 (4)	经常 (5)	总是 (6)

35 在过去 12 个月内， 主要水源能满足您家饮用和做饭吗，时间有几个月？

月数:		不记得 (-1)

36 你经常担心您家里的主要水源不能满足家庭饮用和做饭需求吗(频度)?

从不 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)

37 你家能负担家庭主要水源的水费吗（仅直接支付费用，不包括维护费用）?

不能 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)	他们不需付水费 (6)

38 总体来说，你认为你家里饮水的质量怎样(任何处理前)?

不知道 (1)	特差（2)	很差 (3)	满意 (4)	好 (5)	非常好 (6)

39 你家里有用于农用、果树、家畜饲养或水产养殖（指养鱼）的土地吗?

是，有使用的土地权 (1)	是，有租赁给其他人的权利 (2)
没有，因为租给了别人 (3) *[跳到问题 52]*	没有土地使用权 (4) *[跳到问题 52]*

40 你家里有多少土地用于农业 (用于农作物、草地、树木、果树等)?

亩:		不知道 (-1)	没有，只有畜牧和水产用地 (-2) *[跳到问题 46]*	

43 过去 2 年内，你家每个种植季能生产或购买足够的堆肥/粪便或肥料吗？

家里认为不需要使用堆肥/粪便或肥料 (1)				
不能 (2)	很少 (3)	有时 (4)	经常 (5)	总是 (6)

44 过去 2 年内，你家每个种植季能负担起足够种子的费用吗？

不需要，因为家里留了种子 (1)	不能 (2)	很少 (3)	有时 (4)
经常 (5)	总是 (6)	其它，详细说明 (7):	

45 在旱季/一年中其他时间，你家的农作物通常有足够的水吗？

	旱季		从没 (1)	很少(2)	有时 (3)	经常 (4)
	其他时间		总是 (5)	地区无旱季(6)	极少，或没有作物 (7)

46 在旱季/一年中其他时间，如果你家有家畜，通常有足够的水饲养吗？

旱季		少量或没有家畜(1) *[跳到问题 48]*	从来没有(2)	很少 (3)	
其他时间		有时 (4)	经常 (5)	总是 (6)	本地无旱季 (7)

47 在过去 2 年内，你家通常能提供（种植、收集或购买）足够的饲料吗？

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)

48 在旱季/一年中其他时间，如果你家有水产养殖，通常有足够的水吗？

旱季		少量或没有水产养殖 (1) *[跳到问题 50]*	从没 (2)	很少 (3)	
其他时间		有时 (4)	经常 (5)	总是 (6)	本地无旱季 (7)

49 在过去 2 年内，你家能经常生产或购买足够的鱼料吗？

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)

50 你家通常有足够的人员照看/管理田地 (农作物、果树、林业、家畜和/或水产)吗？

从来没有 (1)	很少 (2)	有时 (3)	经常 (4)	总是 (5)

52 在未来 12 个月内**可能**发生并对您家庭造成不良影响的**事件**中，哪 3 项是您最担心的？
[调查员要在提供的空白处记录 3 条事件，从最担心(52.1) 到最少担心 (52.3)]

53 这些事件中，每个事件对你家庭的影响程度如何？ *[“可能的严重性”]*

54 这些事件中，某个事件在未来 12 个月发生的可能性如何？ *[“可能发生的频度”]*

不知道 (-1) *[跳到问题 59]*	不很担心任何负面事件 (-2) *[跳到问题 59]*		
可能的严重性=	低-小 (1)	中-适度 (2)	高-重大(3)
可能发生的频度=	可能性很小 (1)	可能 (2)	非常可能 (3)

1st	52.1)	write in	53.1) 可能的严重性=		54.1) 可能发生的频度=	
2nd	52.2)	write in	53.2) 可能的严重性=		54.2) 可能发生的频度=	
3rd	52.3)	write in	53.3) 可能的严重性=		54.3) 可能发生的频度=	

55 如果你刚才提及的最害怕的事件*[问题 52 中]*会在未来 12 个月内发生，你家里最可能反应（应对）的 3 个主要办法是什么？

不知道 (-1)	初步策略		第二步策略		第三步策略	

1. 寻找农田外的工作	10. 儿童帮助做比平时耿更多的家庭工作	19.出售储存的谷物	28.延期还债
2. 工作更长时间或从事其他日日工作	11. 请求朋友帮助农活或生意	20.出售牲畜	29.跟亲戚借钱
3. 从事商业	12. 请家人帮助农活或生意	21.使用存款或出售首饰	30.跟朋友借钱
4.削减保健开支	13.依靠当地政府	22.出售耐用品	31.从合作社或村基金借钱(社区来源)
5.减少酒精消费	14.依靠中央政府	23.出售田地	32.从银行或财政服务提供者那里借钱
6.减少肉类消费	15.依靠援助机构	24.出售生意	33.从私人放贷人处借前
7.减少燃料消费	16.依靠团体保险	25.出售／离家(与本地亲戚同住)	34.送儿童出门打工
8.下季少种农作物	17.依靠私人保险	26. 出售／离家 (搬到另外的地方)	35.将儿童带出学校让他们工作
9.将田地租出去	18.寻求技术援助	27. 寻求医疗治疗	36.乞讨求钱／食物
37. 其它，详细说明：			

56 如果你刚才提及的最害怕的事件*[问题 52 中]*会在未来 12 个月内发生，你认为需要多久才能重新回到令人满意的情况？ *[以月数记录答案 (2 年 = 24 个 月)]*

不知道 (–1)	少于 1 月 (–2)	我家里不能恢复 (–3)	月 =	

57 假设在某极端灾难（任何种类）下，你家房子完全毁坏，但家人没有受伤，你家需要多长时间重建房子 *[以月数记录答案(2 年 = 24 个 月)]*

不知道 (–1)	我们将搬家(–2)	我们家的房子不会重建(–3)	月 =	

58 如果你刚才提及的最害怕的事件*[问题 52 中]*会在未来 12 个月内发生，你认为谁最可能帮助你？

没有人 (1)	家人/亲戚 (2)	朋友 (3)	保险公司 (4)
财政机构 (5)	地方政府 (6)	中央政府 (7)	政府(普遍) (8)
援助组织 (9)	不知道 (10)	其它，详细说明 (11):	

59 在过去 12 个月内，因为没有充足的食物，你家有人比平时少吃食物吗？*[如果 "是"，大约多长时间?]*

从不 (1)	是， 1、2 次 (2)	是， 约一周(3)	是， 约几周 (4)
是， 约一月 (5)	是， 约一月多 (6)	是， 大部分日子 (7)	不知道 (8)

61 在过去 12 个月内，你家经历过超过 2 周、且没有足够食物的时候吗？*[如果 "是"， 有多少这样的时段?]*

没有 (1)	是， 1 次 (2)	是，2 次 (3)	是，3 次 (4)
是，4 次 (5)	是， 超过 4 次 (6)	不记得 (7)	其它，详细说明：(8)

62 在过去 12 个月内，你家经历过一整天没有食物的时候吗？ *[如果 "是"， 发生的频度如何?]*

从不 (1)	1、2 次 (2)	大约一月一次(3)
约每 2 周 (4)	约每周 (5)	不知道 (6)

63 在过去12个月内， 你家（大部分成员）经常食用下列食物吗？

.1	谷物 (面包、大米、面团)		1. 从不
.2	根和/或块茎(马铃薯)		2. 很少
.3	蔬菜/绿色食品		3. 大概一月一次
.4	水果		4. 一月很少几次
.5	奶类和/或蛋		5. 一周约一次
.6	肉和/或鱼-海味		6.一周很少几次
.7	坚果和/或豆类（和/或衍生物，豆腐等）		7. 每天
			8. 因宗教或文化原因而不吃

71	你家里有电视吗？*[如果没有，填写 “0”]* 电视机数量

调查时间：______:______

74 您家人经常喝什么水？

桶装水或瓶装水（1）	喝开水（水源为自来水）（2）*[跳到问题 79]*	喝开水（其他水源）（3）*[跳到问题 79]*	喝生水（4）*[跳到问题 84]*	其他，详细说明（5）：*[跳到问题 84]*

75 你家常喝的桶（瓶）装水多少升？

不知道（-1）	一桶（瓶）水 = 升	

76 你家常喝的桶（瓶）装水多少钱？

不知道（-1）	一桶（瓶）水 = 元	

77 你家的桶（瓶）装水是自己去买还是送货上门？

自己买（1）	送货上门（2）	其他（3）详细说明：

78 你家为什么选择喝桶（瓶）装水？[跳到问题 86]

自来水质量不好（1）	没有自来水（2）	经济实惠（3）	安全（4）	口感好（5）	方便（6）	大家都喝桶装水（7）	其他（8）详细说明：

79 你家主要用什么燃料烧水？

干旱季节（冬）	
非干旱季节（夏）	

1. 没有	2. 来自电网[合法或非法连接]稳定电压			
3. 来自电网[合法或非法连接]不稳定电压				
4. 发电机发电	5. 太阳能电池、风轮机或小型水电站的电能			
6. 沼气	7. 煤气（LPG）	8. 天然气	9. 煤油	10. 蜂窝煤
11. 煤/焦炭/褐煤	12. 木炭	13. 动物粪便		
14. 植物油或动物脂肪	15. 蜡烛、固体石蜡或电池供电的其他来源	16. 木头（原木）		
17. 木头（细枝/树枝）	18. 作物秸秆	19. 不知道		

80 你为什么用___烧水?（如果回答“方便”，请说明具体原因。）（问夏天的情况）

需要时，燃料可以获得（1）	家附近可获得燃料（2）	容易运输（3）
火炉成本低（4）	燃料成本低（5）	做饭时容易顺便使用（6）
这种燃料是我们可以支付的，可少量购买（7）	用电方便（8）	其它，详细说明（9）:

81 你家烧开水一般需要多长时间？

不知道（-1）	时常太忙而不烧水（-2）	电热壶分钟数 =	
水壶通常放在炉子上，所以水总是热的（-3）		非电热壶的其它燃料所需要分钟数 =	

82 你家里每天烧多少次开水（喝）？

干旱季节（冬）	
非干旱季节（夏）	

83 当你家烧水时，是将水加热到温热、很热、水开，或者保持水开持续一小段时间？

温热（1）	很热（2）	水开（3）	水开后一段时间（4）	不知道（5）

84 你家平时怎样处理喝的水？

烧开（1）	一般不处理水（2）*[跳到问题 86]*
加热水，但不煮沸（3）	让水静止，以便沉淀后，再加热（4）
过滤/用布过滤（5）	让水静止，以便沉淀(6)
液体漂白剂（7）	漂白粉（8）
液态氯（9）	太阳能消毒（10）
陶瓷过滤（11）	生物砂过滤（12）
膜过滤（13）	净水器（14）
其它，具体说明（15）:	

85		你家平时是谁处理喝的水？

1. 5 岁以下女性	2. 5-14 岁女性	3.15 岁或以上女性	4. 5 岁以下男性	5. 5-14 岁男性
6. 15 岁或以上男性	7. (1) & (2)	8. (2) & (3)	9. (4) & (5)	10. (5) & (6)
11. (3) & (6)	12. 不固定	13. 不知道	14. 其它（说明）:	

86 你家在本地的亲戚有多少人喝开水？

不知道 (1)	没有人 (2)	很少(3)	约一半 (4)	大多数 (5)	所有 (6)

87 你们村/地区有多少家庭饮用开水？

不知道 (1)	没有人 (2)	很少 (3)	约一半 (4)	大多数 (5)	所有 (6)

88 你家如何储存喝的水（包括烧开和未烧开水）？*[平时是否加盖]*

直接喝水龙头水 (1)	将水注入小塑料瓶中 (2)
桶装水，无开关（直接倒） (3)	桶装水，有开关（如饮水机或按压式取水）(4)
储存在未加盖的瓷罐中 (5)	储存在加盖的瓷罐中 (6)
储存在未加盖的金属罐中 (7) [标注什么金属:]	储存在加盖的金属罐中 (8)[标注什么金属:_____]
储存在玻璃容器中 (9)	储存在市售的真空保温瓶中 (10)
储存在加盖的塑料制的容器、桶或简便桶中(11)	储存在未加盖的塑料制的容器、桶或简便油桶中 (12)
储存在配有水拴或龙头的、并加盖容器中 (13)	储存在配有水拴或龙头的未加盖容器中 (14)
不储存 （小矿泉水瓶/直接喝）(15)	其它，详细说明 (16):

89 近期有成人（15 岁以上）喝过没有处理的水吗？

从不 (1) **[跳到问题 91]**	罕有 (2)	偶尔 (3)	经常 (4)	总是 (5)

90 什么时候，成人（15 岁以上）喝没有处理或没有烧开的水？

从不 (1)	没有开水时 (2)	当在田地工作时 (3)	其他工作时 (4)	在学校时 (5)	其它，详细说明 (6):

91 近期有小孩（0~14 岁）喝过没有处理的水吗？

没有小孩 (1) **[跳到问题 93]**	从不 (2) **[跳到问题 93]**	罕有 (3)	偶尔 (4)	经常 (5)	总是 (6)

92 什么时候，小孩（0~14 岁）喝没有处理或没有烧开的水？

从不 (1)	没有开水时 (2)	当在田地工作时 (3)	玩耍时 (4)	在学校时 (5)	其它，详细说明 (6):

93 如果有人喝了没有处理的水，你觉得会发生什么情况？*[选择他们第一个回答的答案]*

没有任何事发生 (1)	如果是雨水，没有任何事发生 (2)
如果是泉水，没有任何事发生 (3)	如果是管井水，没有任何事发生 (4)
他们会生病 (5)	他们会拉肚子 (6)
他们会呕吐 (7)	他们会腹痛 (8)
他们会得伤寒 (9)	他们会得霍乱 (10)
他们会得阿米巴 (11)	其它，详细说明 (12):

94 如果你喝了没有处理过的水，你觉得容易拉肚子吗？

不知道 (1)	不会 (2)	可能会，但不是那么容易(3)	容易 (4)

95 如果拉肚子，对你的影响严重吗？

不知道 (1)	非常小的影响 (2)	中等严重 (3)	非常严重 (4)

96 你觉得怎样喝水会更安全？

烧开 (1)	不知道任何使水更安全的方法 (2)
加热水，但不煮沸 (3)	让水静止，以便沉淀后，再加热 (4)
过滤/用布过滤 (5)	让水静止，以便沉淀(6)
液体漂白剂 (7)	漂白粉 (8)
液态氯 (9)	太阳能消毒 (10)
陶瓷过滤 (11)	生物砂过滤 (12)
膜过滤 (13)	净水器 (14)
桶装水 (15)	其它，具体说明 (16):

97	如果你处理水，是因为什么？*[选择第一个答案]*

家里人不处理水或不烧开水（1）	水不安全，但不知道具体原因（2）	避免疾病（3）
避免胃病（4）	除去微生物 （5）	灭杀微生物(6)
雨水不需处理（7）	除去杂质（8）	其它，详细说明（9）:

98	*【如果不喝桶（瓶）装水，问：】*你觉得你家喝的水质量怎么样？（如果回答“不好”，原因是什么？）

我们认为水质很好（1）	水受到人类排泄物的污染（2）
水本身自然情况下质量低（3）	水受到动物排泄物的污染（4）
水源附近很脏乱（5）	水受到人和动物排泄物的污染（6）
人们在水中洗衣服(7)	水受到工厂化学制剂的污染(8)
水受到农业化肥的污染（9）	水厂处理不到位（10）
不知道质量的好坏（11）	其它，详细说明(12)：

99	你最喜欢喝哪种水： 未处理的水，开水，桶（瓶）装水，其它方式处理过的水（除烧开外的任何方法）？

不知道（1）	未处理（2）	开水（3）	桶（瓶）装水 （4）	其它方式处理（5）	其它，详细说明（6）

100	你愿意买质量好的过滤器来过滤喝的水吗？（过滤后可以直接饮用） 如果愿意，最多愿意花多少钱买？（如果不愿意，为什么？）

不知道（1）	我不会花任何钱，因为这不够重要（2）	我不会花任何钱，因为不想花钱（3）			
100-300 元（4）	300-500 元（5）	500-1000 元（6）	1000 元以上（7）	我们已经买了（8）元	

101	在你家，大部分做饭的地方是：室内、室外或两者都有？

干旱季节		室内（1）	室外 （2）（没有屋顶）
非干旱季节		两者都有 （3）	其它，详细说明（4）:

102	你家平时在哪里烧开水？

干旱季节		室内（1）	室外 （2）	两者都有 （3）	家里不常烧水来喝（4）
非干旱季节		其它，详细说明（5）:			

103	最近两周你拉肚子吗？多少次？**（如果喝桶装水，直接跳到 107 题）**

拉肚子（次）	

104	*【如果不喝桶（瓶）装水：】*你家为什么不喝桶（瓶）装水呢？

太贵（1）	不容易买到 （2）	不安全 （3）	不知道（4）	其它，详细说明（5）:

105	*【如果不喝开水，**跳到 107 题**】*做饭的地方是否与人们在家里时呆着的地方隔开？

不，没有隔开（1）	是，做饭在另外的房间或建筑（2）	是，做饭的地方被门道隔开，并有门或推拉门/布隔离（3）	是，做饭的地方被门道隔开，但没有门/推拉门（4）	其它，详细说明（5）:

106	*[不要询问调查对象，调查员记录厨房如何通风，]*

只是经墙上或屋顶的通风口通风（1）	只经窗户通风（2）	直接通风（只经通向外面的门道通风） （3）	直接通风（经窗户和通向外面的门道通风） （4）
燃料在火炉上燃烧，带有通入室内的管道/烟囱（5）	燃料在火炉上燃烧，带有通向室外的管道/烟囱(6)	机械排风（油烟机[排风扇]）（7）	
间接通风（通风口不直接通向室外） （8）	其它，详细说明 （9）:		

107	*[调查员了解该户洗手处是否提供肥皂/洗手液等清洁产品]*

有，并且看起来经常有人用（1）	有，但看起来并没人经常使用（2）	没有（3）	调查对象不希望调查员看洗手的地方（4）

附加调查问题完成的时间:_____:_____

Appendix II

Data Quality Control

1. Introduction

This annex provides examples of the various methods used to check the internal consistency and quality of the data collected for this study with a focus on the identification of potential outliers.

The full-length document used to record all of these analyses and internal consistency checks is ~150 pages in length. In the interest of conserving space while giving the reader an understanding of the methods used to check and validate the many variables used for the analyses described in Chapters three, four, and five, a selection of examples are provided below.

Figures/graphs and Tables in this appendix (as well as the following appendices) do not have separate captions but are all labeled sufficiently (axis and title/subtitle labels, as well as notes as needed) to allow for interpretation.

For continuous variables, basic tests were conducted to determine whether the distributions were normal (or fit other distributions) and to help identify potential outliers. A great deal of time was spent conducting (logical) "consistency checks" for variables to better understand the various interactions of variables and to help further verify the robustness of the data collected. For example, if it were found that a head of the household was aged 18 but there were four children living in the same HH, this would raise questions about the potential accuracy of the data. For much of this analysis, the specific enumerator identification codes were used to track potential problems by enumerator as well as by question number.

I reviewed the data in two rounds and shared tables of noted issues and potentially illogical associations across variables, with colleagues in Beijing. A system of tables and notation were used to mark potential outliers. The hard-copies of the surveys were checked to determined whether there were errors made during survey scoring, coding, or data entry. In cases where issues could not be resolved, the data were marked as missing.

The first section presents summary statistics and other data concerning the enumerators and the survey durations (time to administer different parts of the survey). This is an example of using outlier identification to examine potential trends across counties, villages, or enumerators to identify possible issues with data reliability (e.g., if the total survey duration was 15 minutes this would warrant further investigation).

The graphs and tables below are excerpts from the broader analysis, provided to give the reader a sense of the initial quality control conducted before the data were used for the analyses presented in chapters three, four, and five. Originally, potential outliers or other issues were highlighted using difference colors; for clarity here, such numbers/cells are shaded in gray or in bold/underlined font.

A standard table format was created and used for this purpose. These tables summarize the "likely" and "possible" outliers, listed by the household's unique identification number, with the value in question placed in parentheses. To the right of these numbers are notes what flagged the observation and why. Below this summary, text is provided to explain in more detail why the cases/observations were flagged and what the resulting investigation revealed and, finally, what decision was reached (as far as ignoring, modifying, or removing the data in question.

2. Examples of quality control checks used

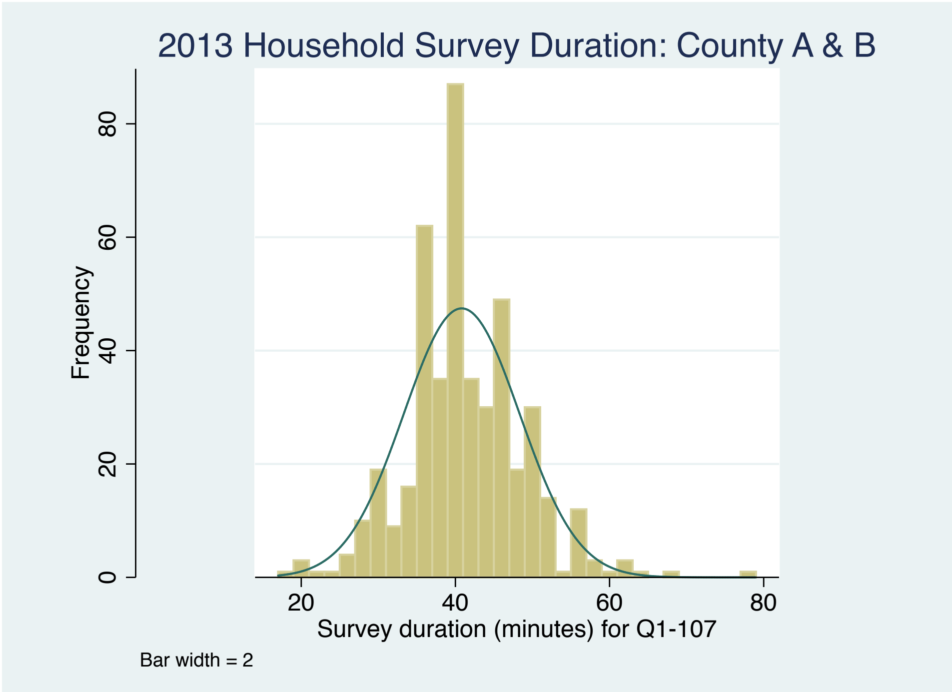
2.1 Enumerators and survey duration data

Number of surveys administered by each enumerator in each village

Village code	Enumerator Code																					
	1	2	3	4	5	6	7	8	9	10	11	12	14	15	16	17	18	19	20	21	22	23
1	4		3			4	4	4	3	4	2	1		1								
2	4	4	4		2	3	4	4	3	2												
3	6	2	4			5	3		1	3	3		3									
4	4	3			4	4	4			4	3		4									
5	4	1			5	4	4		3	3	1		3	2								
6	4	4			4	3	4			3	3			5								
7	5	3		2		3	3			1	4	3	6									
8	3	2		3	3	3	3			2	4	3	4									
9														3	3	1	4	2	5	4	5	3
10														3	4	2	5	3	5	4	4	
11														3	4	3	4	2	6	4	4	
12														3	4	3	4	3	5	4	4	
13														3	4	2	5	3	5	3	5	
14														4	4	3	5	3	6	5		
15														3	4	3	4	3	5	3	5	
Total	34	19	11	5	18	29	29	8	10	22	20	7	20	30	27	17	31	19	37	27	27	3

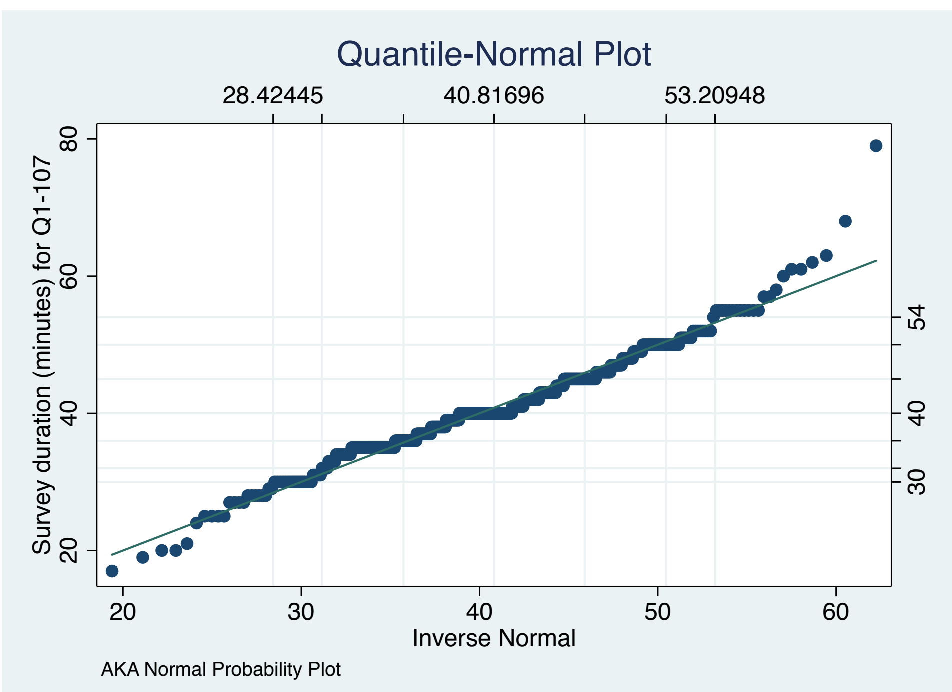
Letter-value display of Total Survey Duration (minutes): Questions 1-107

#	448	Survey duration (minutes)				
M	224.5		40		spread	pseudosigma
F	112.5	36	40.5	45	9	6.6775
E	56.5	34	42	50	16	6.9626
D	28.5	30	41	52	22	7.18259
C	14.5	27.5	41.25	55	27.5	7.401216
B	7.5	25	42	59	34	7.926213
A	4	20	41	62	42	8.746889
Z	2.5	19.5	42.5	65.5	46	8.888633
Y	1.5	18	45.75	73.5	55.5	9.931647
	1	17	48	79	62	10.48131
					# below	# above
inner	fence	22.5		58.5	5	7
outer	fence	9		72	0	1

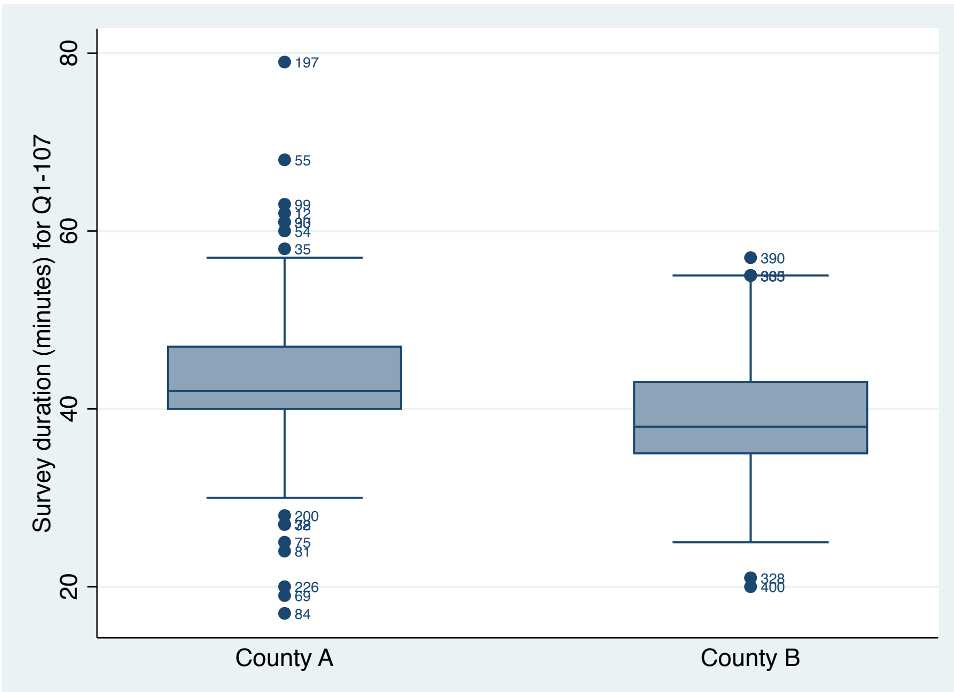


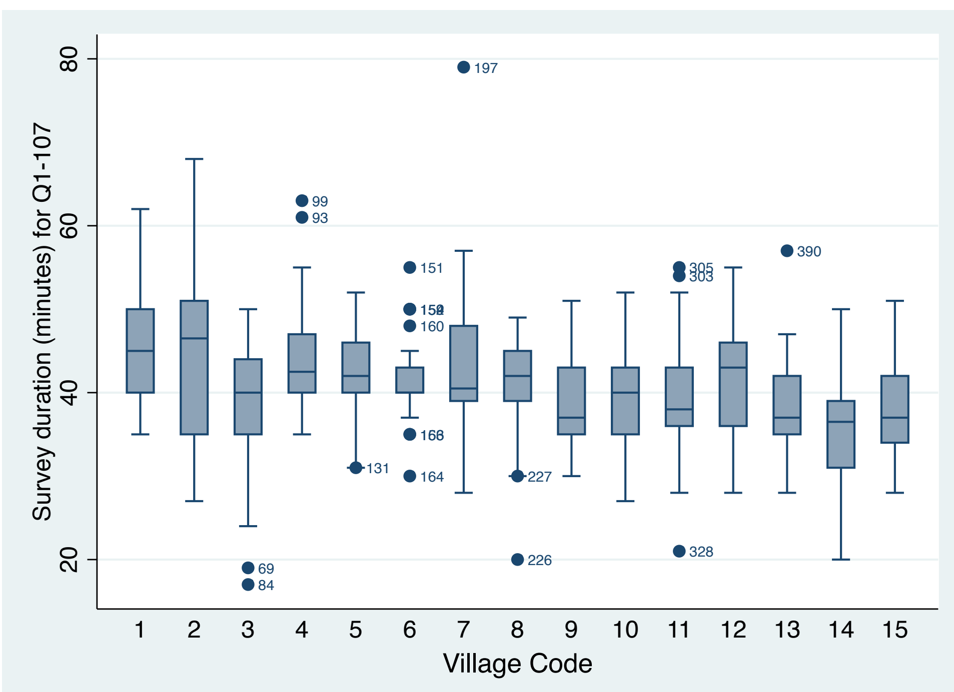
Skewness/Kurtosis tests for Normality: Total survey duration

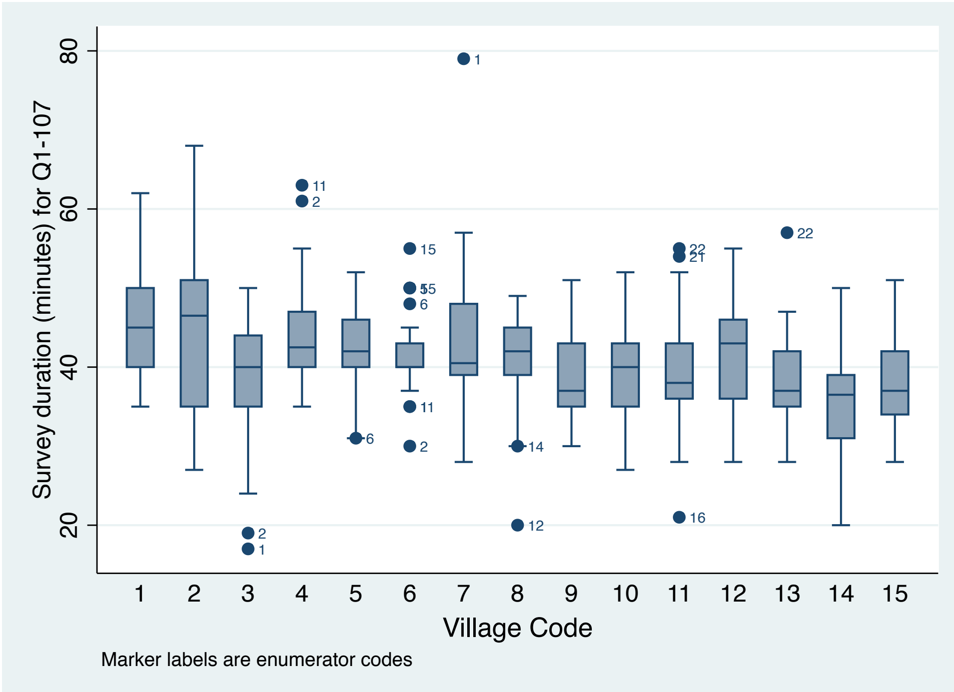
Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
448	0.0007	0.0000	27.26	0.0000



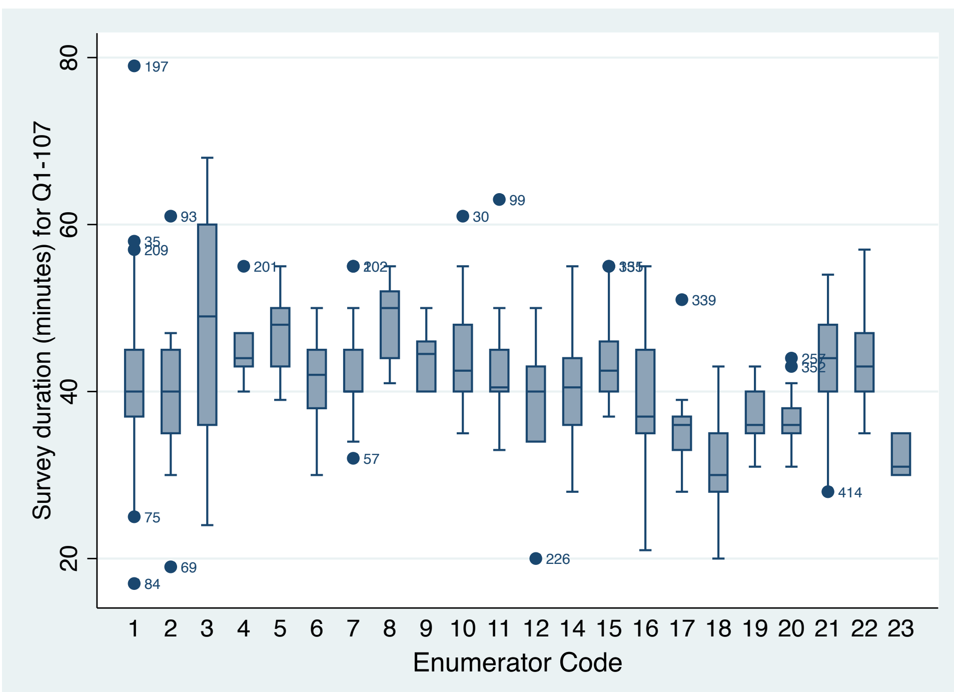
	Total Survey Duration, Questions 1-107: by County							
	min	max	median	mean	sd	skewness	kurtosis	N
County A	17	79	42	42.62083	7.774676	.3820484	5.668819	240
County B	20	57	38	38.73558	6.682755	.2188259	3.105281	208
Total	17	79	40	40.81696	7.534112	.3995572	4.823058	448







Note: Also examined potential outliers of survey duration time by respondent age



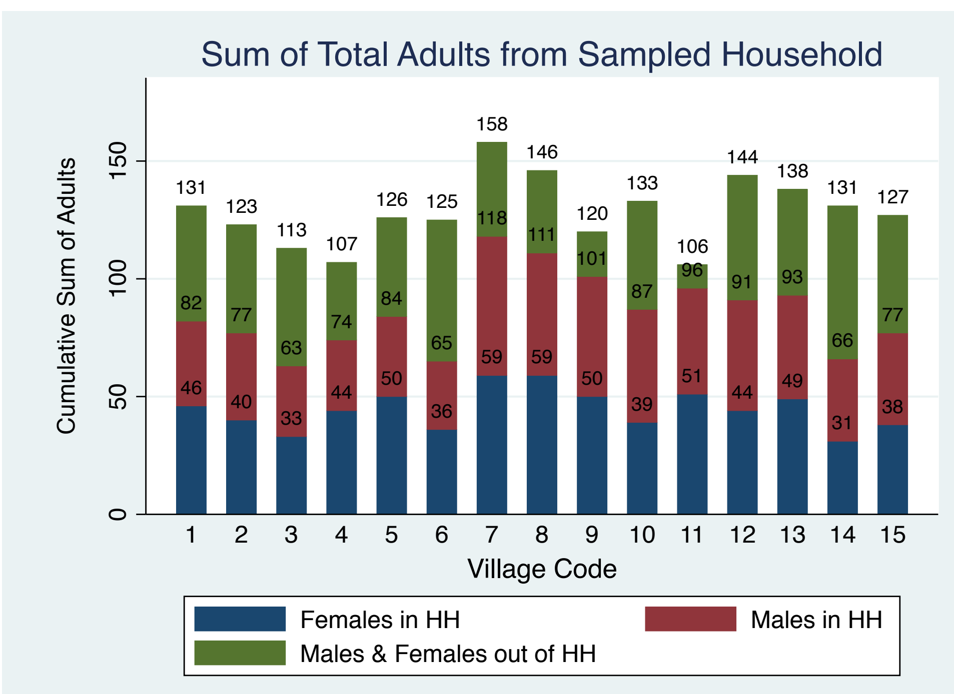
Note: Compare with table above: # of surveys administered by each enumerator in each village

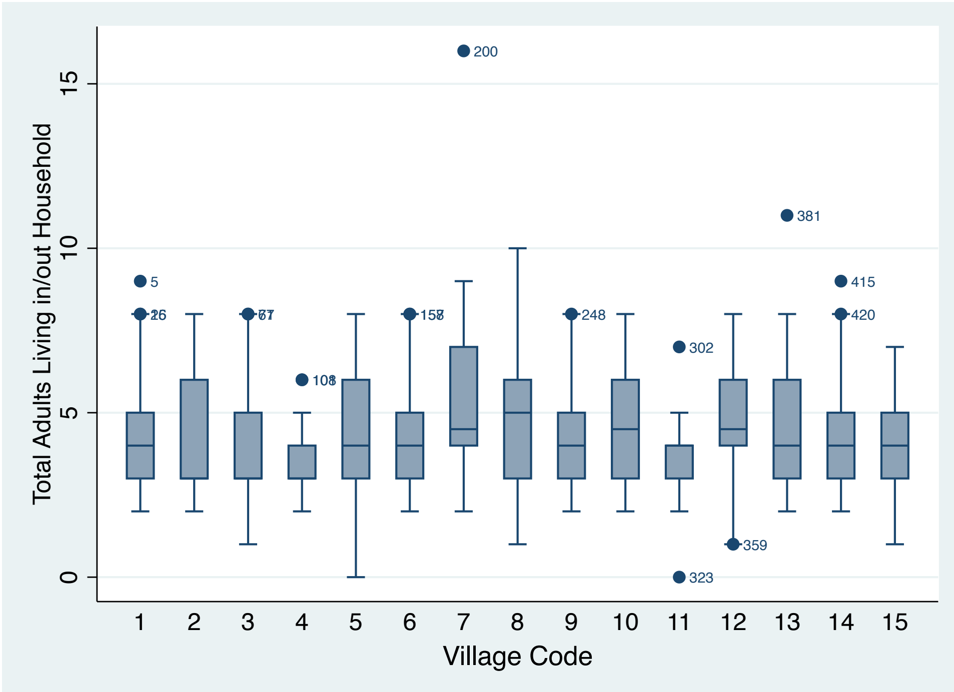
Outlier cases & consistency checks: Household unique identification number (data value)			
Likely	Possible	Issue	Notes
69 (19)	30 (61)	Enumerator #1	Extreme outliers
84 (17)	93 (61)	Enumerator #2	Moderate outliers
197 (79)	99 (63)	Enumerator #18	Short survey times
226 (20)			
328 (21)			
400 (20)			

Notes: For the "likely" cases I examined all the data from each HH and compared to other HHs interviewed by the same numerator. For the times at ~20 minutes or less, I did not see any obvious problems with the data (and all these HH's did not report having children, which activates the skip logic for a number of survey questions, thereby shortening the time), suggesting either they did in fact administer the surveys very quickly and/or they did not accurately enter the survey start and stop times.

Decisions: Unless these cases re-appear in other variables, do not remove outliers.

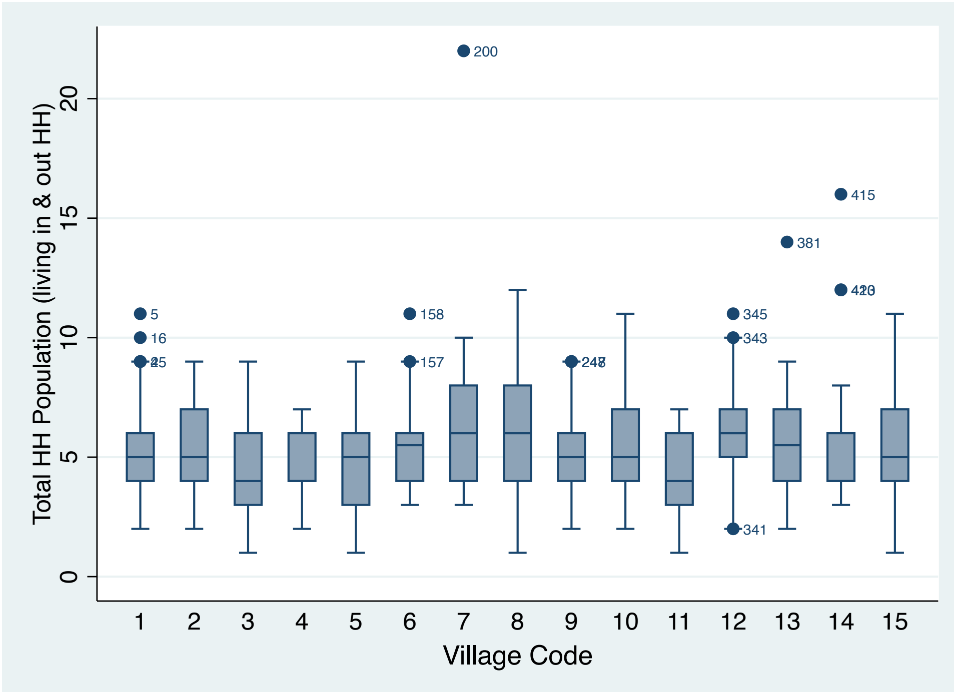
2.2 Household population data

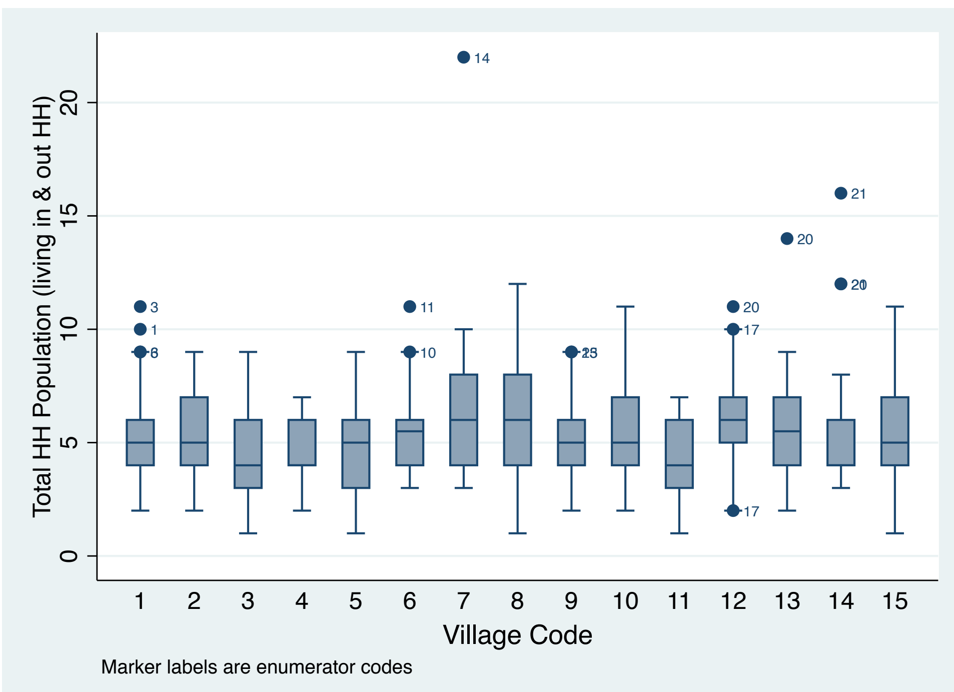




Outlier cases & consistency checks: Household unique identification number (data value)			
Likely	Possible	Issue	Notes
132 (0)		1F 5-14 in HH but, M respondent age 35 [enumerator 7]	Checked during data cleaning – rechecked, ok.
323 (0)		1F 5-14 in HH but, M respondent age 74 [enumerator 18]	Checked during data cleaning – rechecked, ok.
	60 (3)	Q3=3 But M respondent age 71 [enumerator 9]	Found data entry error: Q2.2 should be "1"
	200 (16)		Looks feasible
	381 (11)		Looks feasible

Decisions:
132 (no other issues with this HH so after consultation with NCRWSTG colleagues agree to change Q2.2=1)
323 (no other issues with this HH so after consultation with NCRWSTG colleagues agree to change Q2.2=1)
60 (NCRWSTG colleagues found data entry error, Q2.2 changed to =1)





Note: Potential outliers here already identified and in tables in above sections.

Consistency check: Examining total number of children in HH by Head of HH age

Head of HH age	Total Children in the Household							
	0	1	2	3	4	6	7	Total
20-24	0	0	1	0	0	0	0	1
25-29	3	2	2	0	0	0	0	7
30-34	3	9	10	4	3	0	0	29
35-39	2	13	19	4	0	0	0	38
40-44	15	23	14	4	0	0	0	56
45-49	31	17	5	0	0	0	0	53
50-54	33	16	10	2	3	0	0	64
55-59	22	20	13	6	1	0	0	62
60-64	29	10	13	4	2	2	0	60
65-69	10	11	7	2	1	0	1	32
70-74	15	7	6	1	0	0	0	29
75-79	7	5	3	0	0	0	0	15
80-84	2	0	1	0	0	0	0	3
.m	1	0	0	0	0	0	0	1
Total	173	133	104	27	10	2	1	450

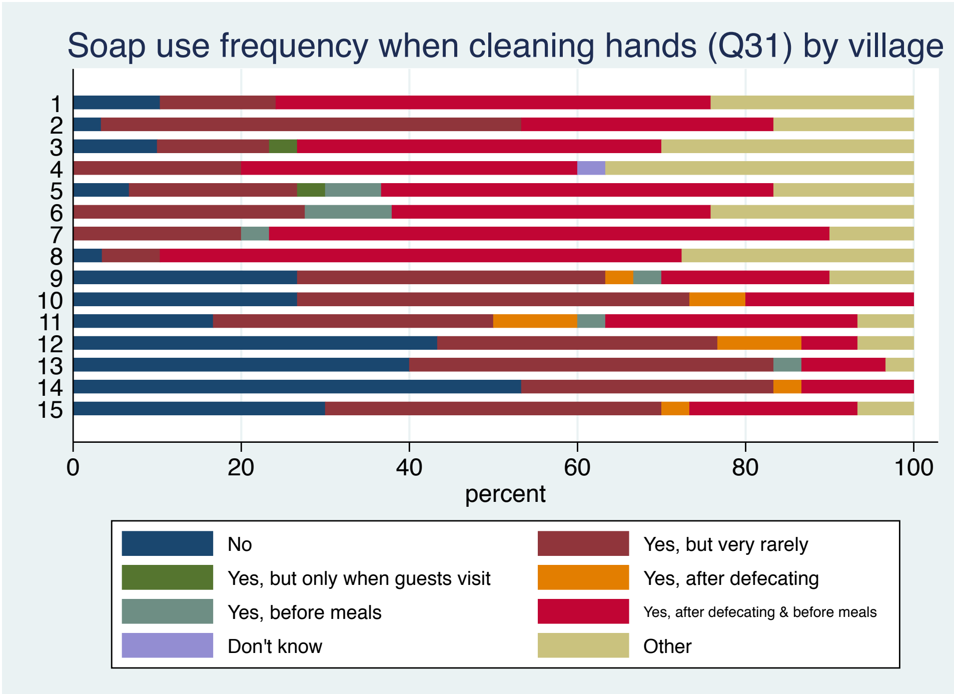
Note: No blatant inconsistencies noted (i.e., young heads of HH have very few children)

2.3 Soap use/frequency for hand-washing

Adult soap use frequency when clean hands (Q31): By county

	County A	County B	Total
No, do not use soap	10	71	81
	4.17	33.81	18.00
Yes, but very rarely	51	79	130
	21.25	37.62	28.89
Yes, but only when guests come	2	0	2
	0.83	0.00	0.44
Yes, after defecating	0	11	11
	0.00	5.24	2.44
Yes, before meals	6	3	9
	2.50	1.43	2.00
Yes, after defecating & before meals	112	36	148
	46.67	17.14	32.89
Don't know	1	0	1
	0.42	0.00	0.22
Other	55	10	65
	22.92	4.76	14.44
.m	3	0	3
	1.25	0.00	0.67
Total	240	210	450

Note: Column frequency and percentages



Cross-check: Reported soap use (Q31, left) and observed presence of soap (Q107, top)

	Yes, likely frequent use	Yes, but unlikely frequent use	No, there is no soap	.m	Total
No, do not use soap	1	10	70	0	81
Yes, but very rarely	24	85	19	2	130
Yes, but only when guests come	0	1	1	0	2
Yes, after defecating	9	2	0	0	11
Yes, before meals	9	0	0	0	9
Yes, after defecating & before meals	104	40	4	0	148
Don't know	0	0	1	0	1
Other	40	20	4	1	65
.m	2	1	0	0	3
Total	189	159	99	3	450

Note: Frequency and column percentages

Note: This suggests that, overall, the self-report data is largely accurate with regard to soap use.

Outlier cases & consistency checks: Household unique identification number (data value)			
Likely	Possible	Issue	Notes
	233 (1)	Q31=1, but Q107=1, Q29=5, Q30=5	No data entry error changed Q31= ".m"
	82, 88, 328	Q107=3, but Q31=6, Q29=5, Q30=5	No data entry error
	449	Q107=3, but Q31=6, Q29=4, Q30=4	No data entry error

Notes: For HHs 82, 88, 328 and 449 they claim they regularly wash their hand with soap, but none was observed, likely due to social desirably bias – so no change.

Decision:
233 (Change Q31= ".m")

2.4 Type of water household usually drinks

Cross-tabulation, HH's primary drinking water source for drinking and cooking (Q32.3, left) and type of water HH usually drinks (Q74, top)

	Bottled W	Boiled tap W	Boiled non-tap W	Non-boiled W	Other	Total
Piped from treatment	48	71	7	10	2	138
	31.17	49.65	9.46	13.33	50.00	30.67
Piped from treatment	5	15	1	2	0	23
	3.25	10.49	1.35	2.67	0.00	5.11
Borehole (> 20m deep)	2	1	0	0	0	3
	1.30	0.70	0.00	0.00	0.00	0.67
Borehole (< 20m deep)	1	1	3	2	0	7
	0.65	0.70	4.05	2.67	0.00	1.56
Private well (> 20m deep)	0	2	1	1	0	4
	0.00	1.40	1.35	1.33	0.00	0.89
Private well (< 20m deep)	0	0	3	5	0	8
	0.00	0.00	4.05	6.67	0.00	1.78
Communal well (> 20m d)	5	15	6	16	1	43
	3.25	10.49	8.11	21.33	25.00	9.56
Communal well (< 20m d)	2	2	2	3	0	9
	1.30	1.40	2.70	4.00	0.00	2.00
Protected spring	2	16	25	28	1	72

	1.30	11.19	33.78	37.33	25.00	16.00
Unprotected spring	0	1	5	3	0	9
	0.00	0.70	6.76	4.00	0.00	2.00
RW harvesting container	0	1	1	0	0	2
	0.00	0.70	1.35	0.00	0.00	0.44
RW harvesting container	7	12	12	2	0	33
	4.55	8.39	16.22	2.67	0.00	7.33
Small dam	3	0	0	0	0	3
	1.95	0.00	0.00	0.00	0.00	0.67
Stream	0	1	0	0	0	1
	0.00	0.70	0.00	0.00	0.00	0.22
Bottled water (delivered)	61	0	1	1	0	63
	39.61	0.00	1.35	1.33	0.00	14.00
Bottled water (collected)	10	0	0	0	0	10
	6.49	0.00	0.00	0.00	0.00	2.22
Other	7	3	7	2	0	19
	4.55	2.10	9.46	2.67	0.00	4.22
.m	1	2	0	0	0	3
	0.65	1.40	0.00	0.00	0.00	0.67
Total	154	143	74	75	4	450
	100.00	100.00	100.00	100.00	100.00	100.00

Note: Frequency and column percentages

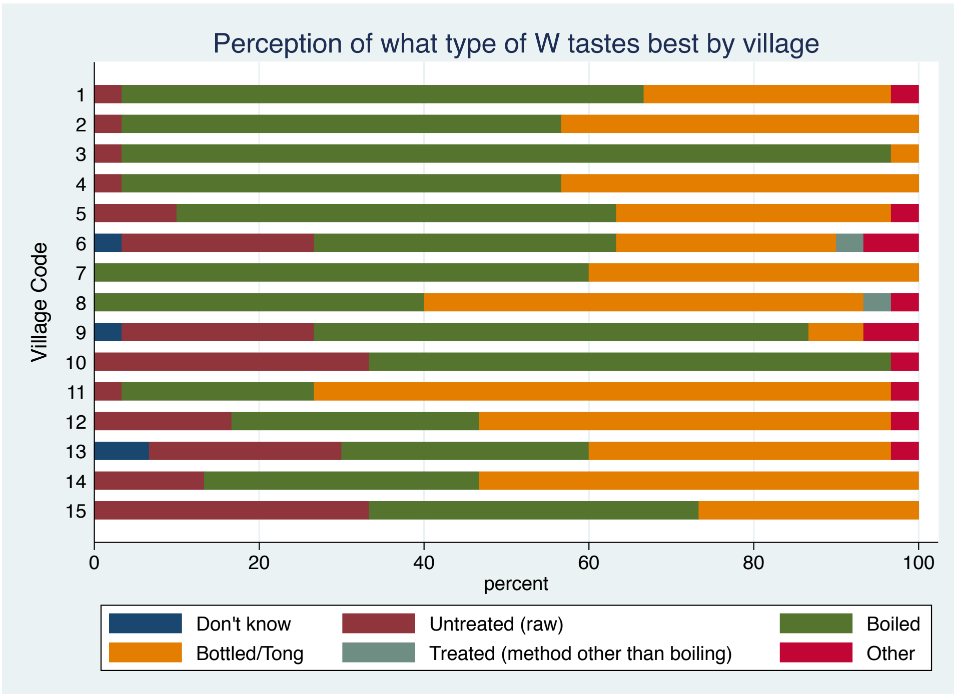
Outlier cases & consistency checks: Household unique identification number (data value)

Likely	Possible	Issue	Notes
398 (3)		Q74=3 but response to Q75, 76, 77	Data entry error
49 (4)		Q32.3=22, but Q74=4 Q34=2, Q84=2, Q88=1	Data entry error on Q32
	216 (5)	Q74=5 but response to Q75, 76, 77	Maybe fill tong w well W?
	168 (2)	Q74=2 but response to Q75, 76, 77	

Notes: The two HH identified via the cross-tabulation table above were 49 and 398. After consultation with NCRWSTG colleagues it seems that HHs 216 and 168 drink both bottled water and boiled water – and for HH 398 there was a data entry error (should have been Q74=1). For HH 49 it appears to be a data entry error for Q32, but there are other issues with the data from this HH also.

Decisions:
216, 168, 398 (Change Q74=1)
49 (keep Q74=4 but change Q32 to MD)

2.5 Perception of what type of water tastes best



Type of water HH usually drinks (Q74)	Perception of which type of W tastes best (Q99) Don't kno	Untreated	Boiled	Bottled/T	Treated (	Other	Total
Bottled W	0	1	8	147	0	1	157
Boiled tap W	0	0	139	1	0	2	142
Boiled non-tap W	1	0	68	1	0	3	73
Non-boiled W	3	55	5	6	2	4	75
Other	0	2	0	0	0	1	3
Total	4	58	220	155	2	11	450

Outlier cases & consistency checks: Household unique identification number (enumerator)

Issue	Notes
158 (11)	Q99=3, Q74=4 (HH drinks untreated water after letting settle, but prefers boiled??)
277 (15)	Q99=3, Q74=4 (HH drinks untreated spring water from tap, but prefers boiled??)
292 (20)	Q99=3, Q74=4 (HH drinks untreated spring water from tap, but prefers boiled??)
294 (20)	Q99=3, Q74=4 (HH drinks untreated spring water from tap, but prefers boiled??)
299 (21)	Q99=3, Q74=4 (HH drinks untreated spring water from tap, but prefers boiled??)
353 (22)	Q99=2, Q74=1 (HH drinks bottled W but prefers taste of untreated – OK)

Notes: After discussing with NCRWSTG agreed that while this may seem a little strange, it is also possible that while these HHs have one preference they do not act on it – no change.

Appendix III

Supporting Material for Chapter III

1. Introduction, missing data, & sample weights

1.1 Overview

This appendix presents statistical summaries, plots, analyses, and model outputs used to conduct the analyses presented in chapter three. "Courier" font is used throughout this appendix because it is a fixed-width font which allows Stata outputs to remain aligned/legible.

Stats outputs are provided often with some information (e.g., summation rows) in the original Stata outputs truncated in order to save space.

Summary statistics are provided for continuous variables and tabulations provided for binary and categorical variables. Cross-tabs were conducted for all new categorical variables to confirm that the coding worked as expected (they are not presented here in an effort to limit the total number of pages). In cases of more complicated variable creation, the additional steps undertaken are described with Stata outputs, and/or graphs, provided as well. In some cases, the variable code names were changed as the analyses progressed and older versions may also be described/listed here.

Throughout this text, household is often abbreviated as "HH". Unless otherwise noted, all test statistics and associated p-values presented below are at the 95% Confidence Level and are two-tailed.

1.2 Missing data and sample weights

Originally, missing data/values were coded as "-99" for the data entry (since this is not a possible value for any survey question/variable). For the analysis, for those cases where there should have been data but was not, this missing data was re-coded from "-99" to ".m" for "Missing Data" (MD). In some cases, question responses which activated skip logic were recoded as ".s" for "skipped" (still treated as MD). In addition, outliers are sometimes labeled with ".o".

In the earlier sections the descriptive statistics for MD are provided, in subsequent sections that provide descriptive statistics and population estimates these are provided without the MD to reflect the estimated percentages of various characteristics/behaviors etc.

Based on the sample size calculations (see Methods Chapter) a total of 450 HHs were to be sampled. Since 30 HHs were to be sampled per village this meant that there was one "extra" village after seven villages were to be selected in each county. Consequently, there was a slightly higher probability for HHs in County A to be sampled than in County B, meaning, for any one HH randomly selected from the entire sample of 450 HHs there is a 53.3% chance that the HH will come from County A versus Count B.

As such, survey weightings are sometimes used in the analyses below, especially when providing population parameter estimates. Specifically, sampling weights were applied using the inverse proportions/probabilities, meaning HHs in County A are weighted at 0.93 and HHs in County B weighted at 1.07 (via a new variable called “SampleWeights_C”).

SampleWeights_C	County Code		
	County A	County B	Total
.9333333	240	0	240
1.066667	0	210	210
Total	240	210	450

1.3 ICC and sampling error

Note: This section will be more easily understood if read after reviewing the definitions and descriptive statistics below.

The intracluster correlation coefficient, aka, intraclass correlation coefficient (ICC), is essentially a way to estimate the ratio of the between-cluster variance over the between and within cluster variance for a given variable. The resulting statistic is referred to using the letter ρ (rho).

A ρ close to one (i.e., where between-cluster variance is quite high) indicates that cluster membership explains a lot/most of the variability; conversely, a small ρ closer to zero implies that within-cluster variance is much greater than between-cluster variance and therefore cluster membership does not explain much of the variability.

The original sample size was based on an estimated boiling prevalence of 68% in the population and our desire to be able to detect a proportion of that size (i.e., .68) within +-5%. Given that ~35% of the HHs sampled drink bottled water this makes our analysis somewhat more challenging because we know that most of these HHs often heat or boil their bottled water before drinking it (usually using the built-in heating device in the bottle holder/base). However, our sample size estimate for boiling prevalence provided by the Guangxi CCDC was 68%.

The study estimates of those that boil and do not drink bottled water is ~48%, and those that drink bottled water ~35%, if we assume at least half of the bottled water drinkers also boil then we arrive at a figure of 65.5% boiling. In order to create a dummy variable to label ~half of these bottled water HHs as boiling in order to explore this further, those HH’s drinking bottled water that also responded to Q87 that “some, about half, or most” of the HHs in their village also boiled were included (n=17, 21, 34 respectively). That is, a total of 72 of the HHs that drink bottled water (out of a total of 157, 156 of whom answered Q87) were included in this new dummy “ICC_D” and considered as boilers. As a result, 64% of the HHs can be considered as boilers (ICC_D=1).

The ICC estimates derived with this new variable are also compared to more lax and stringent inclusion criteria for boiling, below.

```
           |    Cat: Boil-Electric,  Boil-OF, Bottled, Untreated
     ICC_D | Boil w/El  Boil w/OF  Bottled W  Untreated         .m |     Total
-----------+-------------------------------------------------------+----------
         0 |         0          0         85         75          3 |       163
         1 |       122         93         72          0          0 |       287
```

```
Survey: Mean estimation

Number of strata =       2          Number of obs    =     450
Number of PSUs   =      15          Population size  =     448
                                    Design df        =      13

--------------------------------------------------------------
             |             Linearized
             |       Mean   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
       ICC_D |     .63125   .0270528       .572806     .689694
--------------------------------------------------------------
```

Assuming this proxy for likely-boiling were accurate, we would expect (based on the levels of TTC from HH's using bottled water) that those HHs using bottled water and identified as likely boilers would have lower levels of TTC than HHs not identified as likely bottled-water-boilers, and indeed this is what we find (a mean of .45 compared to .57), though the difference is not statistically significant (one-way t-test, p=0.182). That said, this still suggests that, based on our other data, this rough attempt to estimate which HHs among those drinking bottled water also boil their water will likely work sufficiently well for the ICC estimates.

Specifically, the ICC = rho = psi/psi+theta; i.e., between-level variance/(between-level variance + within-level variance). Using ICC_D and the "icc" command in Stata, we see that the ICC = .059

```
Intraclass correlations
One-way random-effects model
Absolute agreement

Random effects: aa3             Number of targets =       15
                                Number of raters  =       30
--------------------------------------------------------------
                 ICC_D |        ICC       [95% Conf. Interval]
-----------------------+--------------------------------------
            Individual |   .0593856       .0172425    .1724275
               Average |    .654463       .3448426    .8620804
--------------------------------------------------------------
F test that
  ICC=0.00: F(14.0, 435.0) = 2.89             Prob > F = 0.000
```

As a confirmation, using ICC_D and the "xtreg" command in Stata, we see that the ICC = .059, suggesting that our ICC estimate (.012) used for the sample size calculation was indeed too low. If we used the maximum likelihood estimation "MLE" option (instead of the random effects "RE" option) the ICC = .054 (CI=.016-.142).

```
Random-effects GLS regression                   Number of obs      =       450
Group variable: aa3                             Number of groups   =        15

R-sq:  within  = 0.0000                         Obs per group: min =        30
       between = 0.0000                                        avg =      30.0
       overall = 0.0000                                        max =        30

                                                Wald chi2(0)       =         .
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =         .

------------------------------------------------------------------------------
       ICC_D |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .6377778   .0374966    17.01   0.000     .5642858    .7112698
-------------+----------------------------------------------------------------
     sigma_u |  .11748443
     sigma_e |  .46756891
         rho |  .05938558   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Note on Stata output: For the MLM models, the between-level (between clusters/villages) SD is listed under the coefficient ("Coef.") for "/sigma_u" (and indicated in the models with *psi*); the within-level (within clusters/villages) SD is listed for "/sigma_e" (and indicated in the models with *theta*).

What this means concretely is that had we used a rho (ICC) of .059 instead of .012 for our sample size calculation the Design Effect would have been 2.711 (instead of 1.29) and therefore the appropriate sample size would have been ~906, essentially double that of our actual sample size. However, if we relax our effect size criteria very slightly from the ability to detect a +-5% difference to a +-6% difference (as is also done for the power estimates below) while the design effect remains the same at 2.711 the sample size needed is ~630, which is still larger than our sample size of 450, but the difference is not as extreme as at the 5% level. For an effect size of 7% the required sample size decreases again to ~462 which is very close to the actual sample size of 450.

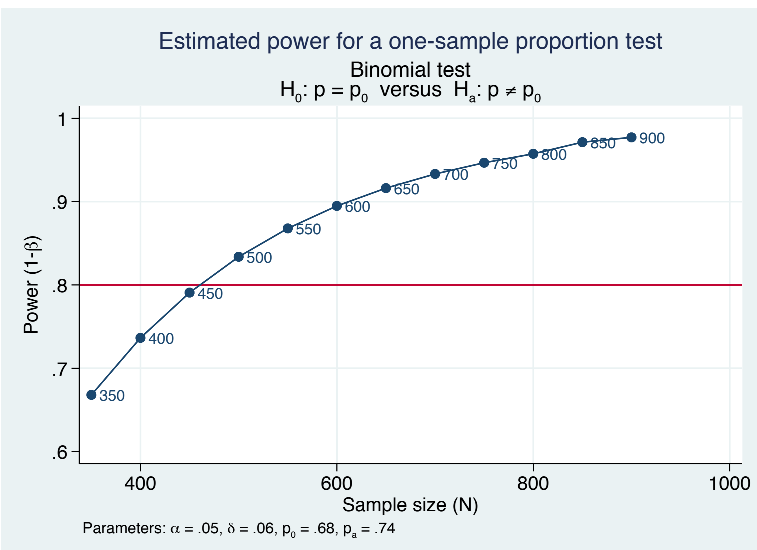
1.4 Power and post-implementation sample size estimates

If we want to see how much power or sample has to detect a +-5% difference between the expected proportion of HHs that boil (68%) and the actual population proportion we find that our study has a power equal only to .63. That is, beta, the probability of a Type II error (missing an effect when there is one) is 37%.

If we want to set beta to 20% (.2, so power=.8) with an alpha of .5 in order to determine the sample size needed to detect at least a 5% difference between the expected proportion of HHs that boil (68%) and the actual proportion then we would have needed a sample size of 664. Conversely, if we set a lower bar and wish to only be able to detect a difference of +-6% then our resulting power = .79 which is essentially at the conventional threshold value of power at .8.

Assuming the ability to detect a 6% difference then we would need a sample of 458 which is essentially the sample size we have (n=450). While this test is predicated on the assumption that the observations are independent, and we know that clustering has an impact on observation independence, putting this aside for the moment we can say that our study is powered to find a ~6% difference between the expected 68% of HHs that boil and the actual percentage/proportion and that our sample size is ~sufficient to achieve this level of power. Thus, at this level, the probability of a Type II error (missing an effect when there is one) is ~21%.

In order to illustrate the relationship between various sample sizes and levels of power, the graph below shows sample sizes from 350 to 900 at intervals of 50 HHs and the corresponding level of power, based again on an expected proportion of .68 and the ability to detect a difference of +-.06, with beta=.2. Here we see that, assuming observations are independent (which is problematic given the small but meaningful influence clustering), our sample size of 450 is just at the .8 power threshold and the gains in power from increasing sample size past ~550 begin to diminish (as the curve flattens out). At all these levels while the specified alpha is constant at .05 the estimated alpha is <.05 in all cases (ranging from .043 to .048).



1.5 Sampling error estimation using CCDC data

Another method of examining the effectiveness of our random sampling approach and data collection is to compare key demographic data from our surveys (administered during the summer of 2013) with government data also collected in 2013. The expectation is that there will be differences in the estimates, but if the differences are not large (and the standard deviations in-line with that of the government data) this provides additional evidence that our data is representative of the larger population.

The Guangxi Province CCDC offices in County A and County B provided village-level averages for basic demographic characteristics compiled from data collected at healthcare centers in the counties. The tables below show the average values from this data, the survey data, and the differences.

County Means	**Mean number of adults per HH**			**Mean number of children per HH**			**Percentage male-headed HHs**			**Mean head of HH age**		
	C	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**
A	3.8	3.5	0.2	1.0	1.1	-0.1	82.0	71.7	10.3	42.3	51.0	-8.8
B	3.4	3.6	-0.2	0.8	1.1	-0.3	83.9	96.2	-12.3	57.6	54.0	3.7
Column mean	**3.6**	**3.6**	**0.0**	**0.9**	**1.1**	**-0.2**	**82.9**	**83.1**	**-0.3**	**49.4**	**52.4**	**-3.0**
Column SD	**0.6**	**0.5**	**0.7**	**0.3**	**0.2**	**0.4**	**12.8**	**16.0**	**20.6**	**11.1**	**3.1**	**11.6**

Key: C=CCDC data | S=Survey data | D=Difference (CCDC minus survey)

Fortunately, this indicates that our random sampling approach was effective and since our survey data for these key demographics is closely aligned with the government census data this suggests that our parameter estimates based on other survey variables are likewise representative of the larger population.

Village code	**Mean number of adults per HH**			**Mean number of children per HH**			**Percentage male-headed HHs**			**Mean head of HH age****		
	C	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**
1	4.6	3.6	1.0	1.2	1.1	0.1	94	83	11	31	53	-22
2	4.1	3.3	0.8	1.4	1.2	0.2	95	60	35	30	53	-23
3	4.0	2.9	1.1	1.6	0.8	0.8	97	55	42	32	57	-25
4	3.2	3.0	0.2	0.8	0.8	0.0	73	77	-4	49	48	1
5	3.1	3.5	-0.4	0.8	0.8	0.0	68	83	-15	51	47	4
6	3.8	3.2	0.6	0.9	1.3	-0.4	83	55	28	50	47	3
7	4.0	4.6	-0.6	0.7	1.3	-0.6	65	80	-15	49	50	-1
8	3.7	4.3	-0.6	0.8	1.3	-0.5	81	80	1	46	54	-8
Column mean	**3.8**	**3.5**	**0.2**	**1.0**	**1.1**	**-0.1**	**82.0**	**71.7**	**10.3**	**42.3**	**51.0**	**-8.8**
Column SD	**0.5**	**0.6**	**0.7**	**0.3**	**0.2**	**0.4**	**12.6**	**12.6**	**22.3**	**9.4**	**3.7**	**12.5**

Key: C=CCDC data | S=Survey data | D=Difference (CCDC minus survey)

Village code	**Mean number of adults per HH**			**Mean number of children per HH**			**Percentage male-headed HHs**			**Mean head of HH age**		
	C	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**	**C**	**S**	**D**
9	2.6	3.7	-1.1	0.8	1.1	-0.3	83	100	-17	53	53	1

10	3.0	3.7	−0.7	0.7	1.1	−0.4	86	100	−14	56	54	2
11	2.6	3.4	−0.8	0.5	0.8	−0.4	54	83	−29	65	56	9
12	4.1	3.9	0.1	0.8	1.1	−0.3	93	100	−7	55	55	0
13	4.1	3.9	0.2	1.4	1.1	0.2	97	97	0	51	53	−2
14	3.4	3.3	0.1	0.8	1.2	−0.4	90	100	−10	57	55	2
15	4.0	3.4	0.6	0.7	1.0	−0.3	84	93	−9	67	52	14
Column mean	**3.4**	**3.6**	**-0.2**	**0.8**	**1.1**	**-0.3**	**83.9**	**96.2**	**-12.3**	**57.6**	**54.0**	**3.7**
Column SD	**0.7**	**0.2**	**0.6**	**0.3**	**0.1**	**0.2**	**14.1**	**6.2**	**9.3**	**6.1**	**1.4**	**5.9**

Key: C=CCDC data | S=Survey data | D=Difference (CCDC minus survey)

Assuming the clustering effect is not significant then our study is powered to detect a +-6% difference in the actual proportion of HH's that boil (~64%) as compared to the expected/predicted proportion (68%) at a power of .79, meaning there is a ~21% chance we will commit a Type II error and not diagnose an actual effect; furthermore, at this level our estimated alpha (significance level) is .043 which is very close, and more conservative, than the specified level of .05.

Looking only at the sample size calculation based on the ICC, however, and looking at the actual ICC from our data (since none was available during study design), we see that the design effect is much larger than anticipated and at an effect size of +-5% we would have needed a sample of ~900. However, if we make our effect size slightly more liberal and use a +-6% effect size then based on our ICC calculations we would have needed a sample size of ~630; extending this one step further, with an effect size of +-7% a sample size of ~460 would have been sufficient - which is very close to our actual sample of 450.

Further evidence of the robustness of our sample is provided by comparing summary statistics for key demographic variables from government Guangxi CCDC county-level data and our sample, where we find that our sample data is very closely assigned with the means and standard deviations from the CCDC data, suggesting our sample is indeed representative of the larger population from which it was taken.

2. Variables

2.1 Dependent variables for drinking water quality

38 cases (8.5% of the total of 444 HHs with TC and TTC data) with likely coliform-data-related outliers were identified and removed for the bulk of

the analysis below. However, much of the initial analysis below provides data with and without these outliers included; and similarly, part of the sensitivity analysis for the final model also examined the differences with and without outliers.

Most of these outliers, 31 cases, were identified because the concentration of TC were very high (above 2,000 MPN/100mL) but the corresponding TTC of the same sample/HH was either below the detection limit (BDL) or less than 2 MPN/100mL. Though there are a great number of environmental sources for TC, and most (but not all) of the TTCs are of human or animal fecal origin, we expect to see that in HHs where there are especially high counts of TC, relatively high levels of TTC are likewise detected. This rationale is also justified by research on microbial indicators in the subtropics (Chao et al., 2003).

These cases, where TC was greater than 2,000 MPN/100mL but TTC was less than 2 MPN/100mL or BDL, are listed below by the HH unique identification number as well as the village code (aa3 column) and the TC and TTC data; here, a zero corresponds to a measurement of BDL.

80.5% (n=25) of these 31 outliers are from County A with the remaining 20% (n=6) from County B. This difference may be partially due to errors in water sampling and testing protocol and/or may reflect the overall higher prevalence of TC and TTC contamination in County A as compared to County B.

28.5% (n=2) were from County A and the remaining 71.5% (n=5) from County B. Again, errors in following water sampling and testing protocol are suspected as a likely cause.

In addition to these 38 outlier cases, there was MD for five HHs for the TC data and six HHs for the TTC data (and all five of the MD cases for TC overlap with MD for TTC) – see tables immediately below. In summary then, for 90.2% of the sample (n=406) the coliform data was used for most of the analysis below.

__Dummy: Outlier case=1, none=0	Freq.	Percent	Cum.
Cases w/no coliform outliers	406	90.22	90.22
Cases w/coliform outliers	38	8.44	98.67
.m	6	1.33	100.00
Total	450	100.00	

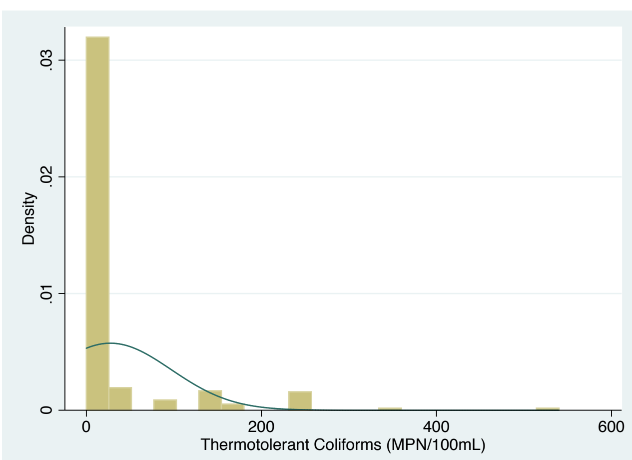
__Dummy: Outlier case=1, none=0	Dummy: TC detected=1, No TC=0 No TC (BD	TC detect	.m	Total
Cases w/no coliform o	28	378	0	406
Cases w/coliform outl	0	38	0	38
.m	0	1	5	6

Total	28	417	5	450

__Dummy: Outlier case=1, none=0	Dummy: TTC detected=1, No TTC=0 No TTC (B	TTC detec	.m	Total
Cases w/no coliform o	241	165	0	406
Cases w/coliform outl	31	7	0	38
.m	0	0	6	6
Total	272	172	6	450

Fortunately, the distribution of outliers by enumerator shows that the 38 outlier cases for water quality data appear to be randomly distributed across the sample. When we calculate the percentage of outlier cases per total cases for each enumerator the average is 9.7% (SD=9.3%). Looking at these proportions of outlier cases to total HHs enumerated, three enumerators have especially high rates of outlier cases; namely, enumerators four (40%), nine (20%), and 14 (20%). However, since none of these enumerators were flagged during the initial quality control and consistency check process (and so none of these three were flagged for model sensitivity analysis below) this does not appear to be of particular concern.

In order to induce linearity in the relationship between Y and X (since the regression models below are predicated on a linear relationship) the Y (TTC) was log transformed. Since TTC data from rural areas are generally very heavily right skewed (due to so many cases which are BDL) the convention is to log-10 transform such data before analyzing it. Indeed, as can be seen below in the histogram for the TTC data it is heavily right skewed.



That said, it is sometimes important to present summary statistics for TTC in both raw/original and logged scales.

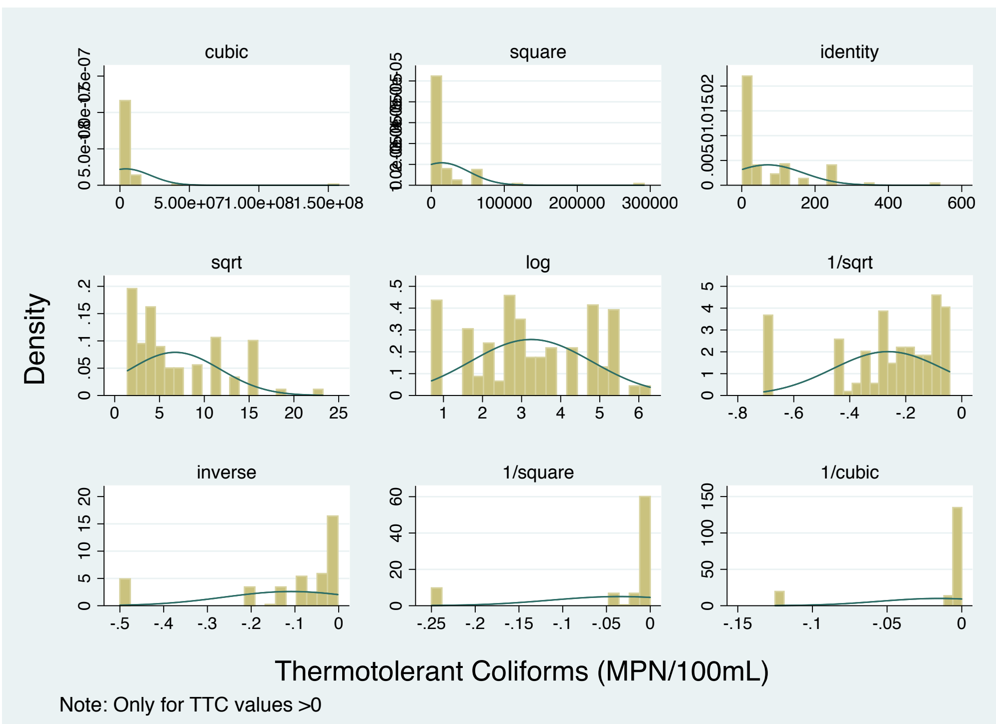
> "Theoretical considerations show that risks are directly proportional to the arithmetic mean of the ingested [pathogen] dose. Hence, arithmetic means of variables such as concentration in raw water, removal by treatment and consumption of drinking-water are recommended. This recommendation is different from the usual practice among

microbiologists and engineers of converting concentrations and treatment effects to log-values and making calculations or specifications on the log-scale. Such calculations result in estimates of the geometric mean rather than the arithmetic mean, and these may significantly underestimate risk. Analysing site-specific data may therefore require going back to the raw data rather than relying on reported log-transformed values."

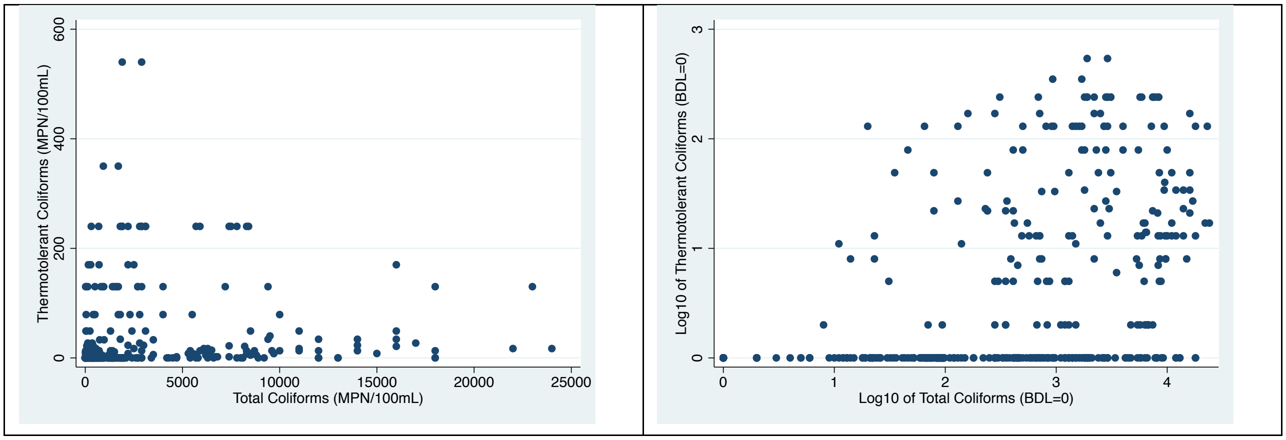
(WHO, 2004: 131)

As such, summary statistics for the untransformed coliform data are presented at various points in this annex, though most of the primary graphs of note show coliform data on a logged scale.

Rather than simply starting with a log-10 transformation (as is the convention) a number of possible transformations were first explored as illustrated below.

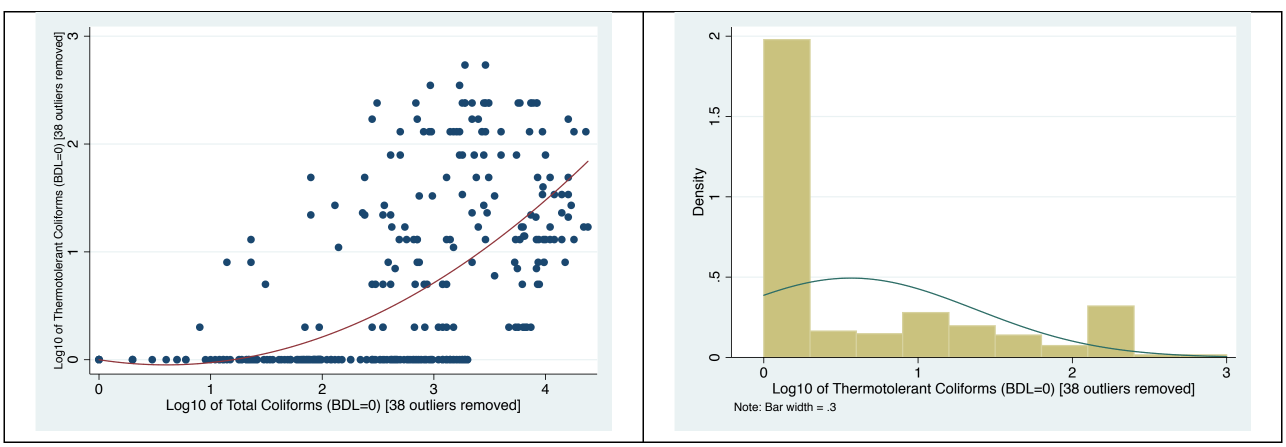


Since we expect to see a relationship between the TC and TTC data, such that as TC concentrations increase so to do TTC concentrations, we can use this to help provide a visual check with regard to the effectiveness of the transformations by graphing TTC coliforms (Y axis) against the TC coliforms (X axis) as shown below in the untransformed form and log-10 transformed.

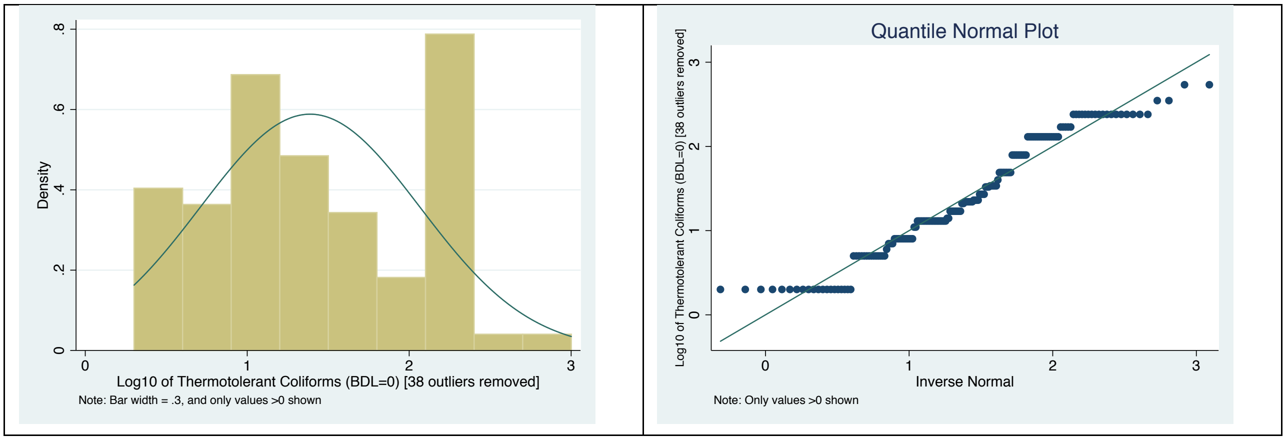


Due to the right-skewed nature of the data generally, and especially the TTC data, it is difficult to visually see this trend. After exploring different options for transformations it seemed that a log transformation would indeed be appropriate, and rather than using a natural log transformation a log-10 transformation was used, since this is the convention when transforming coliform data. The graph below shows the same plot of TTC against TC but now with the log-10 transformed data; the relationship between TTC and TC is now much clearer as a result, and the many cases of TTC BDL cluster at zero on the X axis, but spread out along different values of TC.

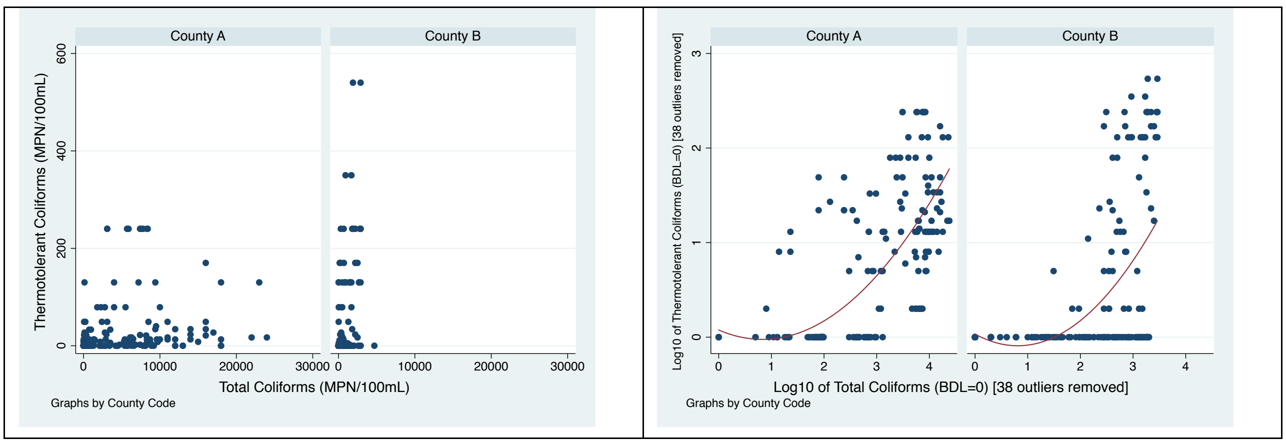
When we look at this same plot but without the 38 outlier cases identified above removed, the plot looks much the same, but there are fewer cases above log 3.5 TC on the X axis. A line of best fit is also superimposed which shows the expected overall relationship such that as TC concentrations increase so too do TC concentrations. Now, when we graph a histogram of the logged TTC data with the outliers removed it is still heavily right skewed but we can better see the distribution of the non BDL data points.



Just for the sake of visualization, if we again graph the histogram but this time excluding all the BDL cases we get an even clearer understanding of the data's distribution and its deviation from a normal curve (though here it appears much more normal), and similarly the corresponding quantile-normal plot shows that much of the transformed data is now approaching a normal distribution.



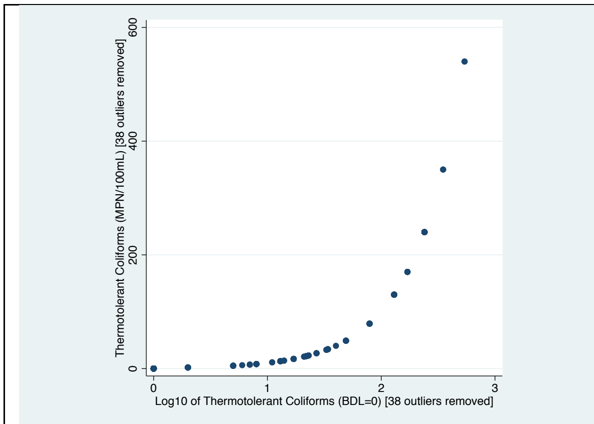
When we examine the relationship between TTC and TC by county using the raw data (with outliers) it is difficult to quickly see a relationship.

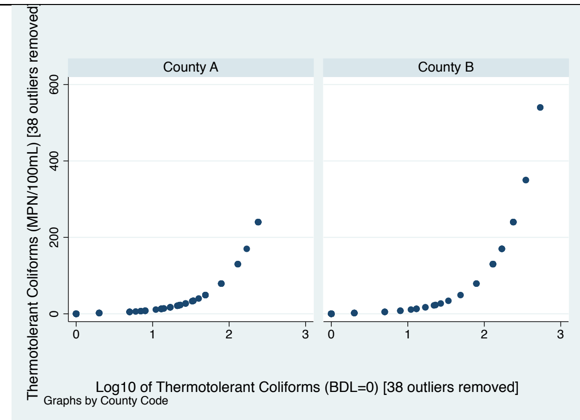


However, as above, when we plot the log-10 transformed data with and without the outliers we see that this same relationship (as TTC increases so does TC) is evident in both counties when examined separately, which is what we would expect).

The result then is not ideal, in that the data is not distributed perfectly normally, but in light of the heavily skewed distribution this transformation is far superior to the raw data, for the purposes of our analysis below (and a natural log transformation is not much different); moreover, most of the analysis below does not require a normally distributed DV, especially given the sufficiently large sample size of 406-444 (without and with outliers).

As a final visual example/confirmation, we can plot the raw TTC data against the transformed TTC data.





2.2 Independent variables & other variables

This section provides a summary of the covariates used in the analysis below, with and without outliers in some cases, and for those newly created covariates their distributions across both counties are provided as well as consistency checks (cross-tabulations) with the original survey questions upon which they were built. The section headings start with the variable name used in Stata (which is also shown in much of the Stata output and models below). "Dummy" variables are binary variables usually with a zero and a one, the one value reflecting the name of the variable. The format and definitions for each entry are quite consistent so text-based explanations are provided only as needed.

2.2.1 TC_cont_D & TC_cont_D_or - Dummy: TC Detected=1, No TC (BDL)=0

Based on raw TC data, if Below Detection Limit (BDL) then = 0, if any TC=1

ALL DATA

Dummy: TC detected=1, No TC=0	County Code: County A	County B	Total
No TC (BDL)	4	24	28
	1.67	11.43	6.22
TC detected	231	186	417
	96.25	88.57	92.67
.m	5	0	5
	2.08	0.00	1.11

OUTLIERS REMOVED

```
  Dummy: TC |
detected=1, |
No TC=0 (38 |
   outliers |      County Code
   removed) |  County A   County B |     Total
------------+----------------------+----------
No TC (BDL) |         4         24 |        28
            |      1.67      11.43 |      6.22
------------+----------------------+----------
TC detected |       204        175 |       379
            |     85.00      83.33 |     84.22
------------+----------------------+----------
         .m |         5          0 |         5
            |      2.08       0.00 |      1.11
------------+----------------------+----------
         .o |        27         11 |        38
            |     11.25       5.24 |      8.44
```

2.2.2 TTC_cont_D & TTC_cont_D_or - Dummy: TTC Detected=1, No TTC (BDL)=0

Based on raw TTC data, if Below Detection Limit (BDL) then = 0, if any TTC=1

ALL DATA

```
  Dummy: TTC |
 detected=1, |      County Code
    No TTC=0 |  County A   County B |     Total
-------------+----------------------+----------
No TTC (BDL) |       127        145 |       272
             |     52.92      69.05 |     60.44
-------------+----------------------+----------
TTC detected |       107         65 |       172
             |     44.58      30.95 |     38.22
-------------+----------------------+----------
          .m |         6          0 |         6
             |      2.50       0.00 |      1.33
```

OUTLIERS REMOVED

```
  Dummy: TTC |
 detected=1, |
No TTC=0 (38 |
    outliers |      County Code
    removed) |  County A   County B |     Total
-------------+----------------------+----------
No TTC (BDL) |       102        139 |       241
             |     42.50      66.19 |     53.56
-------------+----------------------+----------
TTC detected |       105         60 |       165
             |     43.75      28.57 |     36.67
-------------+----------------------+----------
```

.m	6	0	6
	2.50	0.00	1.33
.o	27	11	38
	11.25	5.24	8.44

Note: Confirmation against TTC_cont_D

Dummy: TTC detected=1, No TTC=0	Dummy: TTC detected=1, No TTC=0 (38 outliers removed)				
	No TTC (B	TTC detec	.m	.o	Total
No TTC (BDL)	241	0	0	31	272
TTC detected	0	165	0	7	172
.m	0	0	6	0	6
Total	241	165	6	38	450

2.2.3 TreatDW_D - Dummy: Treat(boil or bottled)=1, Untreated=0

Dummy created based on Q74:

Dummy: Treat(boil or bottled)=1, Untreated=0	Type of water HH usually drinks (Q74)					
	Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Untreated W	0	0	0	75	0	75
Treat DW (boil or bot	157	142	73	0	0	372
.m	0	0	0	0	3	3
Total	157	142	73	75	3	450

2.2.4 Boil_D - Dummy: Boil (any method)=1, Don't boil (bottled or untreated)=0

Confirmation based on Q74 and Q84:

Method HH usually uses to treat DW (Q84)	Type of water HH usually drinks (Q74)					
	Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Heat to boil	0	139	72	0	0	211
Don't usually treat D	0	0	0	66	3	69
Heat partially (not t	0	2	0	0	0	2
Let W stand so partic	0	0	0	3	0	3
Other	0	0	0	2	0	2
.m	0	1	1	4	0	6

	Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
.s	157	0	0	0	0	157
Total	157	142	73	75	3	450

Confirmation based on Q74 and Q99:

Perception of which type of W tastes best (Q99)	Type of water HH usually drinks (Q74) Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Don't know	0.00	0.00	1.37	4.00	0.00	0.89
Untreated (raw)	0.64	0.00	0.00	73.33	66.67	12.89
Boiled	5.10	97.89	93.15	6.67	0.00	48.89
Bottled/Tong	93.63	0.70	1.37	8.00	0.00	34.44
Treated (method other	0.00	0.00	0.00	2.67	0.00	0.44
Other	0.64	1.41	4.11	5.33	33.33	2.44
Total	100.00	100.00	100.00	100.00	100.00	100.00

2.2.5 Bottled_D - Dummy: Bottled=1, Other (Boil, untreated)=0

Dummy created based on Q74:

Dummy: Bottled=1, Other=0	Type of water HH usually drinks (Q74) Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Not bottled	0	142	73	75	0	290
Bottled	157	0	0	0	0	157
.m	0	0	0	0	3	3
Total	157	142	73	75	3	450

2.2.6 BlBtUn – 3-category variable: Boil=1, Bottled=2, Untreated=3

Dummy created based on Q74:

Cat: Boil, Bottled, or Untreated	Type of water HH usually drinks (Q74) Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Boil	0	142	73	0	0	215
Bottled	157	0	0	0	0	157
Untreated	0	0	0	75	0	75
.m	0	0	0	0	3	3
Total	157	142	73	75	3	450

2.2.7 BlBtUn and Bl2BtUn – 3 & 4-category variables: Boil w/electricity=1, Boil w/other fuel=2, Bottled=3, Untreated=4

First, created a dummy "ElecFuel_D" based on Q79 (=1 if fuel source for boiling is electricity [Q79=2 or 3]:

Dummy: Electricity=1, Other Fuel=0	Freq.	Percent	Cum.
Boil w/other fuel	93	20.67	20.67
Boil w/electricity	122	27.11	47.78
.s	235	52.22	100.00
Total	450	100.00	

Confirm based on Q79:

Fuel used for boiling water (Q79)	Dummy: Electricity=1, Other Fuel=0 Boil w/ot	Boil w/el	.s	Total
Stable voltage electr	0	118	0	118
Unstable voltage elec	0	4	0	4
Biogas	2	0	0	2
Liquid Petroleum Gas	10	0	0	10
Natural gas	2	0	0	2
Wood (logs)	11	0	0	11
Wood (twigs/branches)	61	0	0	61
Crop residue	4	0	0	4
.m	3	0	0	3
.s	0	0	235	235
Total	93	122	235	450

Confirm based on BlBtUn:

Dummy: Electricity=1, Other Fuel=0	Cat: Boil, Bottled, or Untreated Boil	Bottled	Untreated	.m	Total
Boil w/other fuel	93	0	0	0	93
Boil w/electricity	122	0	0	0	122
.s	0	157	75	3	235
Total	215	157	75	3	450

Then used ElecFuel_D to create 4-category Bl2BtUn, based also on Q74 (OF = other fuel):

```
  Cat: Boil-Electric, |
    Boil-OF, Bottled, |      County Code
            Untreated |  County A   County B |     Total
----------------------+----------------------+----------
   Boil w/Electricity |        65         57 |       122
                      |     27.08      27.14 |     27.11
----------------------+----------------------+----------
            Boil w/OF |        66         27 |        93
                      |     27.50      12.86 |     20.67
----------------------+----------------------+----------
            Bottled W |        87         70 |       157
                      |     36.25      33.33 |     34.89
----------------------+----------------------+----------
          Untreated W |        20         55 |        75
                      |      8.33      26.19 |     16.67
----------------------+----------------------+----------
                   .m |         2          1 |         3
                      |      0.83       0.48 |      0.67
----------------------+----------------------+----------
                Total |       240        210 |       450
                      |    100.00     100.00 |    100.00
```

Confirm based on Q74:

```
               Cat: |
     Boil-Electric, |
  Boil-OF, Bottled, |         Type of water HH usually drinks (Q74)
          Untreated | Bottled W  Boiled ta  Boiled no  Non-boile      Other |     Total
--------------------+-------------------------------------------------------+----------
Boil w/Electricity |         0         82         40          0          0 |       122
 Boil w/Other fuel |         0         60         33          0          0 |        93
         Bottled W |       157          0          0          0          0 |       157
       Untreated W |         0          0          0         75          0 |        75
                .m |         0          0          0          0          3 |         3
--------------------+-------------------------------------------------------+----------
             Total |       157        142         73         75          3 |       450
```

2.2.8 ImprovedSource_D – Dummy: Improved Source (~JMP definitions)=1, Unimproved=0

Note: This dummy variable is based on responses to Q32.3 – the "during most of the year". Q32.3 response 1, 2, 3, 5, 7 and 11 were coded as improved (1), and all other responses as unimproved (0); this classification is roughly based on the JMP's definition of an improved source. Spring water was considered unimproved because based on additional analysis it seemed quite clear that the enumerators and/or respondents did not always understand the meaning of "protected" spring versus a regular/unprotected.

However, this remains a somewhat problematic variable because Q32 is asking about the primary water source used for both drinking and cooking, and many HHs have different water sources of drinking and cooking.

This especially applies to HHs drinking bottled water, since 72 of the 157 HHs reported a primary water source other than bottled water. However, bottled water was treated as an unimproved source, so this variation would potential balance out among HHs who reported drinking bottled water in Q74.

Primary drinking water source - most of year (Q32.3)	Type of water HH usually drinks (Q74) Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Piped from treatment	49	70	7	10	2	138
Piped from treatment	5	15	1	2	0	23
Borehole (> 20m deep)	2	1	0	0	0	3
Borehole (< 20m deep)	1	1	3	2	0	7
Private well (> 20m d	0	2	1	1	0	4
Private well (< 20m d	0	0	3	5	0	8
Communal well (> 20m	6	15	6	16	0	43
Communal well (< 20m	2	2	2	3	0	9
Protected spring	2	16	25	28	1	72
Unprotected spring	0	1	5	3	0	9
RW harvesting contain	0	1	1	0	0	2
RW harvesting contain	7	12	12	2	0	33
Small dam	3	0	0	0	0	3
Stream	0	1	0	0	0	1
Bottled water (delive	62	0	0	0	0	62
Bottled water (collec	10	0	0	0	0	10
Other	7	3	7	2	0	19
.m	1	2	0	1	0	4
Total	157	142	73	75	3	450

As a sensitivity analysis, two dummy variables were created based on Q32.3, one with bottled water as an unimproved source based on Q32.3 (ImprovedSource_D), and one that did not use any data from the 157 HHs who reported drinking bottled water in Q74 (ImprovedSourceNBW_D). When we look at the absolute percentages (not factoring in the MD) we see that the percentage of HH's that have an improved source is ~48% when we treat bottled water as an unimproved source and use Q32.3 to create the dummy, and it is 52% when we exclude bottled water HHs altogether (and since we lose these 157 HHs this is the primary contributor to our n decreasing from 446 to 290).

Dummy: Improved=1, Unimproved=0	Freq.	Percent	Cum.
WITH BOTTLED WATER			
Unimproved (~JMP definition)	233	52.24	52.24
Improved (~JMP definition)	213	47.76	100.00
WITHOUT BOTTLED WATER			
Unimproved (~JMP, no BW)	139	47.93	47.93
Improved (~JMP, no BW)	151	52.07	100.00

Dummy: Improved=1,	Type of water HH usually drinks (Q74)					
Unimproved=0	Bottled W	Boiled ta	Boiled no	Non-boile	Other	Total
Unimproved (~JMP defi	94	36	57	45	1	233
Improved (~JMP defini	62	104	16	29	2	213
.m	1	2	0	1	0	4
Total	157	142	73	75	3	450

Of the 157 HHs that drink bottled water, if included in the dummy variable the source water of 94 HHs (~60%) would be considered unimproved, with the remaining 62 (~40%) as improved. When we look at the mean TTC of only HHs that drink bottled water (Q74=1) we see that the mean value is close to the same, at ~27 MPN/100mL. When we repeat the analysis with all outliers for the TTC data there is a difference of 3 MPN/100mL in the means (with improved sources being lower).

ImprovedSource_D	min	p50	max	mean	sd	skewness	N
Unimproved (~JMP	0	0	540	28.06977	80.06083	4.079852	86
Improved (~JMP d	0	0	350	27.15385	73.79659	3.102058	52
Total	0	0	540	27.72464	77.48782	3.778594	138

WITH OUTLIERS

ImprovedSource_D	min	p50	max	mean	sd	skewness	N
Unimproved (~JMP	0	0	540	26.23913	77.68963	4.236912	92
Improved (~JMP d	0	0	350	23.14754	68.72647	3.426912	61
Total	0	0	540	25.00654	74.02867	4.009744	153

Considering these factors, I decided to keep the bottled water HHs in the dummy variable, ImprovedSource_D, thus the overall frequencies are:

Dummy: Improved=1, Unimproved=0	County Code County A	County B	Total
Unimproved (~JMP defi	90	143	233
	37.50	68.10	51.78
Improved (~JMP defini	146	67	213
	60.83	31.90	47.33
.m	4	0	4
	1.67	0.00	0.89
Total	240	210	450
	100.00	100.00	100.00

2.2.9 SoapUsed_D – Dummy: HH frequently uses soap=1, Does not (or no soap)=0

Dummy created based on Q107:

Presence of soap by hand-washing area (Q107)	Dummy: Soap present & used=1, If not=0 No soap,	Soap regu	.m	Total
Yes, likely frequent	0	189	0	189
Yes, but unlikely fre	159	0	0	159
No, there is no soap	99	0	0	99
.m	0	0	3	3
Total	258	189	3	450

2.2.10 SoapPresent_D – Dummy: HH has soap=1, Does not (or no soap)=0

Dummy created based on Q107:

Presence of soap by hand-washing area (Q107)	Dummy: Soap present=1, If not=0 No soap	Soap pres	.m	Total
Yes, likely frequent	0	189	0	189
Yes, but unlikely fre	0	159	0	159
No, there is no soap	99	0	0	99
.m	0	0	3	3
Total	99	348	3	450

2.2.11 SafeStorage_D – Dummy: Safe W Storage=1, Unsafe=0

Dummy created based on Q88 (Q88=other treated as MD):

Drinking Water Storage Method	Dummy: Safe storage=1, Unsafe=0 Unsafe W	Safe W st	.m	Total
Drink straight from t	0	52	0	52
Small plastic bottle/	7	0	0	7
19L bottle, w/o base/	27	0	0	27
19L bottle, w base/sp	0	117	0	117
Uncovered clay pot	2	0	0	2
Clay pot w/cover	0	14	0	14
Uncovered metal pot	1	0	0	1
Metal pot w/cover (or	0	46	0	46
Glass container	14	0	0	14
Vacuum flask/thermos	0	47	0	47
Covered plastic conta	0	72	0	72
Uncovered plastic con	3	0	0	3
Covered container w/s	0	6	0	6
Uncovered container w	1	0	0	1
Drink W immediately f	0	5	0	5
Other	0	0	26	26
.m	1	0	9	10
Total	56	359	35	450

2.2.12 VerySafeStorage_D – Dummy: Very Safe W Storage=1, Unsafe=0

More stringent inclusion criteria for this dummy variable:
Dummy created based on Q88 (Q88=other treated as MD):

Drinking Water Storage Method	Dummy: Very Safe storage=1, Unsafe=0 Unsafe (o	Very Safe	.m	Total
Drink straight from t	0	52	0	52
Small plastic bottle/	7	0	0	7
19L bottle, w/o base/	27	0	0	27
19L bottle, w base/sp	0	117	0	117
Uncovered clay pot	2	0	0	2
Clay pot w/cover	14	0	0	14
Uncovered metal pot	1	0	0	1
Metal pot w/cover (or	46	0	0	46
Glass container	14	0	0	14
Vacuum flask/thermos	0	47	0	47
Covered plastic conta	72	0	0	72
Uncovered plastic con	3	0	0	3

Covered container w/s	0	6	0	6
Uncovered container w	1	0	0	1
Drink W immediately f	0	5	0	5
Other	0	0	26	26
.m	1	0	9	10
Total	188	227	35	450

2.2.13 HandwashBM_D – Dummy: Often or Always wash=1, Other=0

Dummy created based on Q29:

Handwashing freq. before meal (Q29)	Dummy: Often or always wash before meal=1, other=0		
	Don't fre	Often or	Total
Never	4	0	4
Rarely	4	0	4
Sometimes	62	0	62
Often	0	154	154
Always	0	225	225
Don't know	1	0	1
Total	71	379	450

2.2.14 HandwashPD_D – Dummy: Always wash=1, Other=0

Dummy created based on Q30:

Handwashing freq. post defecation	Dummy: Always wash after defecation=1, other=0		
	Not alway	Always	Total
Rarely	3	0	3
Sometimes	43	0	43
Often	154	0	154
Always	0	248	248
Don't know	2	0	2
Total	202	248	450

2.2.15 HandwashPD_OA_D – Dummy: Often or Always wash=1, Other=0

Less stringent inclusion criteria for this dummy variable:
Dummy created based on Q30:

Handwashing freq. post defecation	Dummy: Often or always wash after defecation=1, other=0: Don't fre	Often or	Total
Rarely	3	0	3
Sometimes	43	0	43
Often	0	154	154
Always	0	248	248
Don't know	2	0	2
Total	48	402	450

2.2.16 SafeToilet_D – Dummy: Safe=1, Other=0

Dummy created based on Q23:

HH's Toilet Facility	Dummy: Safe toilet=1, Other=0: Other	Safe/Sani	.m	Total
None, open defecation	3	0	0	3
Open pit, communal	15	0	0	15
Enclosed pit, communa	4	0	0	4
Enclosed improved-ven	4	0	0	4
Enclosed pour-flush C	3	0	0	3
Compost or biogas C	1	0	0	1
Open pit, private	21	0	0	21
Enclosed pit, private	13	0	0	13
Enclosed improved-ven	0	22	0	22
Enclosed pour-flush P	0	306	0	306
Enclosed flush P	0	50	0	50
Compost or biogas P	0	7	0	7
.m	0	0	1	1
Total	64	385	1	450

2.2.17 BasicHealthAccess – Continuous - Time to reach clinic that can provide basic healthcare (Q11)

Q11 measures the number of minutes needed to arrive (by any method) at the nearest health center that can address basic illness or injury and thus serves as a proxy for access to basic healthcare. There were three HHs which reported that the health center was too far to reach, all in village eleven; however the mean number of minutes for village eleven (excluding these three HHs) is only 3.7 (SD=1.5) with a max of 5 minutes, so the values from these three HHs were treated as MD.

Minutes to reach health center which can provide basic healthcare

----

	Percentiles	Smallest		
1%	1	1		
5%	2	1		
10%	3	1	Obs	443
25%	5	1	Sum of Wgt.	443
50%	10		Mean	11.33409
		Largest	Std. Dev.	10.75531
75%	15	60		
90%	30	60	Variance	115.6766
95%	30	60	Skewness	2.376749
99%	60	80	Kurtosis	10.64394

2.2.18 VillageIncome (2012, government data)

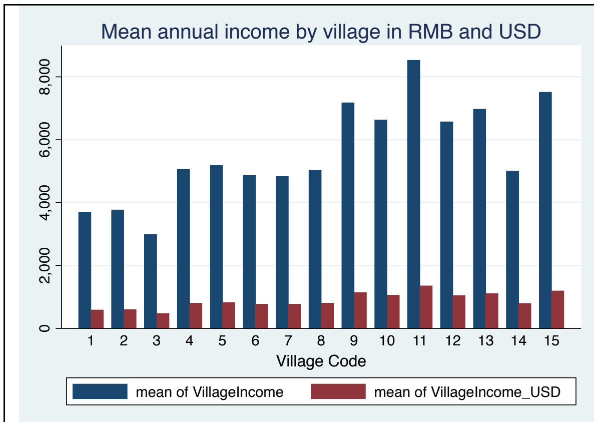
Note: Conversions to USD based on 2012 average exchange rate: USD 1 = RMB 6.3

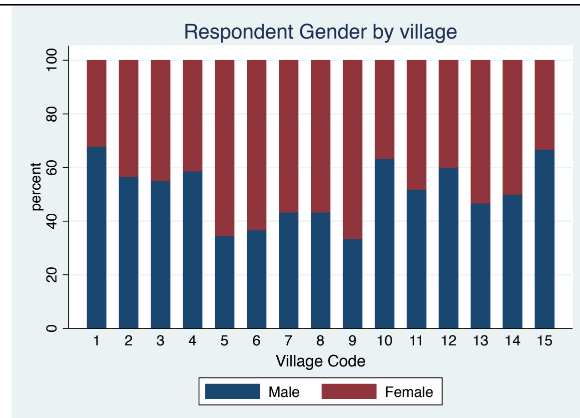
	Mean, RMB	Mean, USD
County A	4425	702
County B	6911	1097

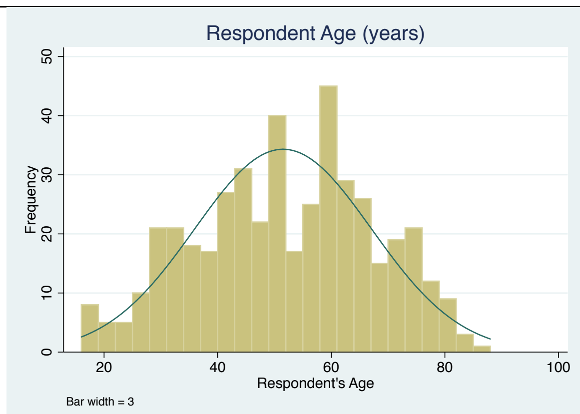
Village Code	Mean, RMB	Mean, USD
1	3698	586.9841
2	3768	598.0952
3	2984	473.6508
4	5052	801.9048
5	5179	822.0635
6	4868	772.6984
7	4830	766.6667
8	5021	796.9841
9	7175	1138.889
10	6630	1052.381
11	8526	1353.333
12	6570	1042.857
13	6970	1106.349
14	5000	793.6508
15	7510	1192.063
Total	5585.4	886.5714

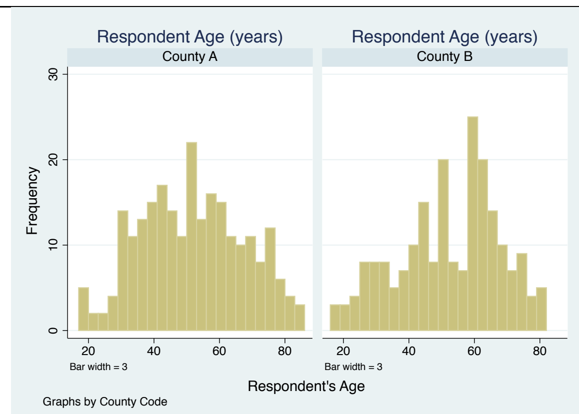
3. Descriptive statistics

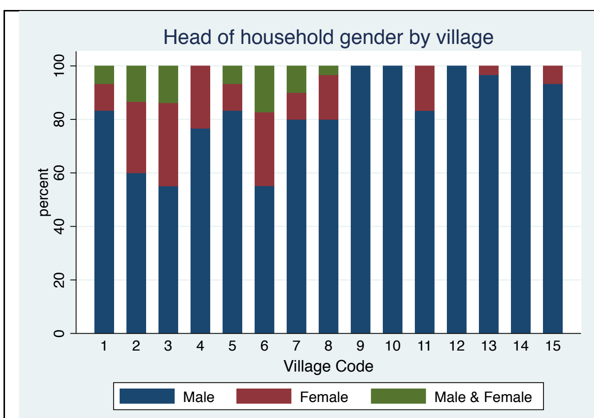
An earlier version of this Appendix included ~70 pages of graphs and tables provided descriptive/summary statistics for the variables used in the chapter three (and chapters four and five in cases) analyses. However, because many of these variables are also discussed in the chapters, and in the interests of conserving space in what are already relatively long appendices, this section has been largely truncated, with a few graphical examples provided below.

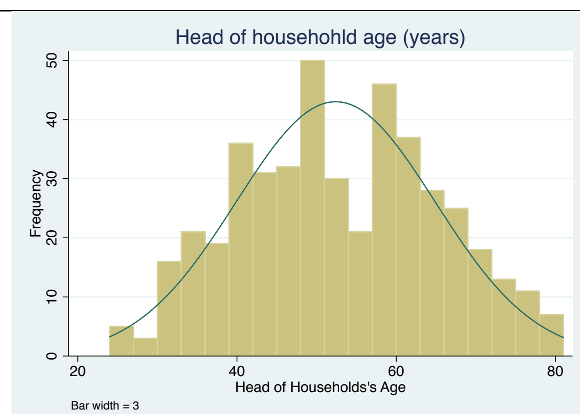


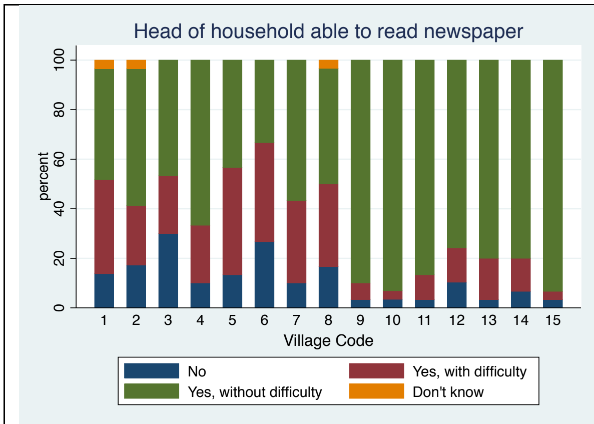


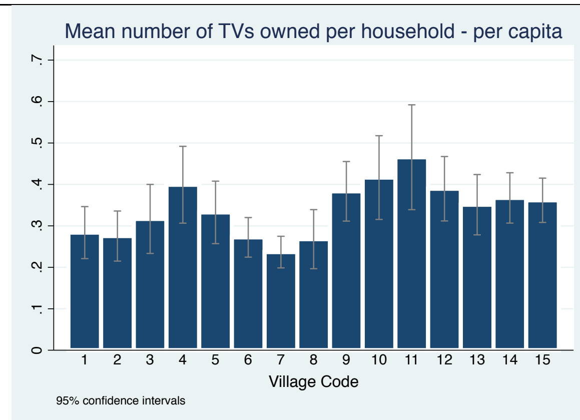


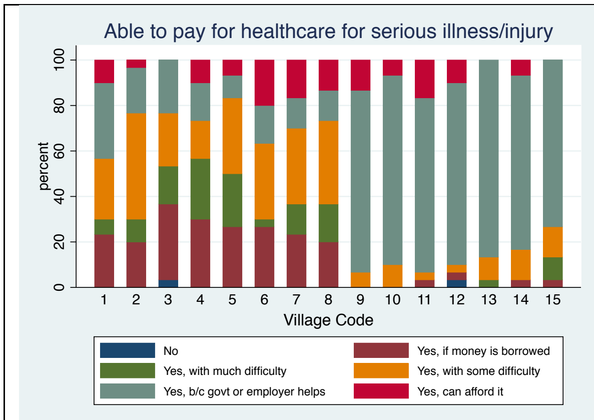


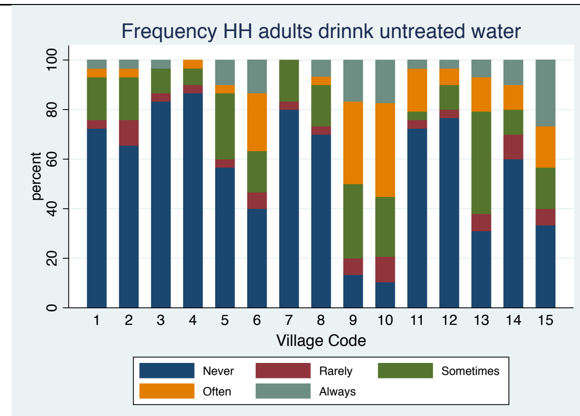


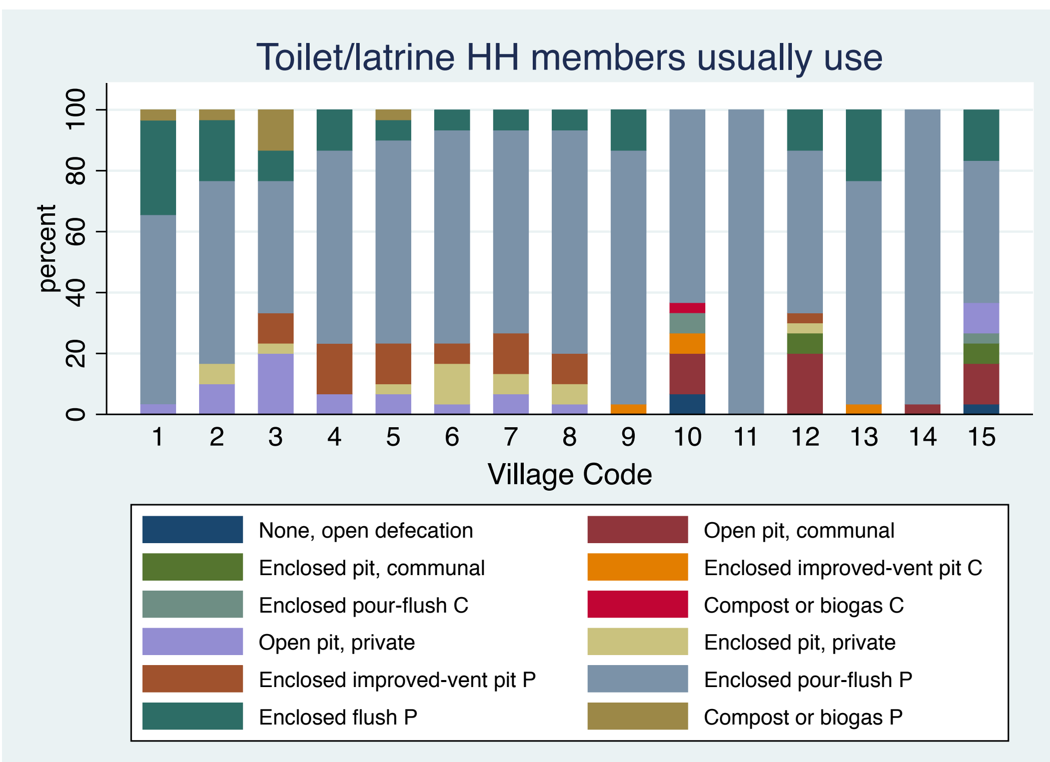


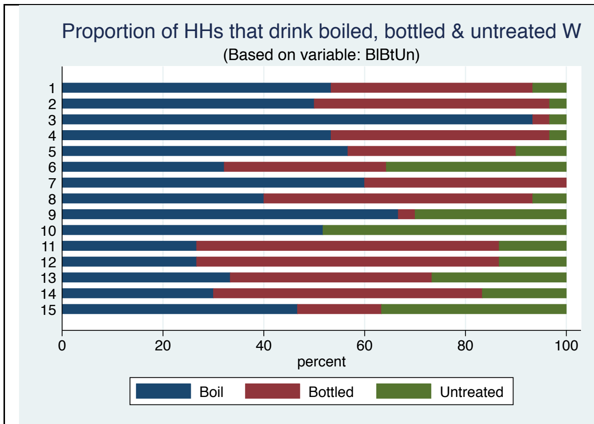

Head of household able to read newspaper
percent
0
20
40
60
80
100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Village Code
No
Yes, with difficulty
Yes, without difficulty
Don't know

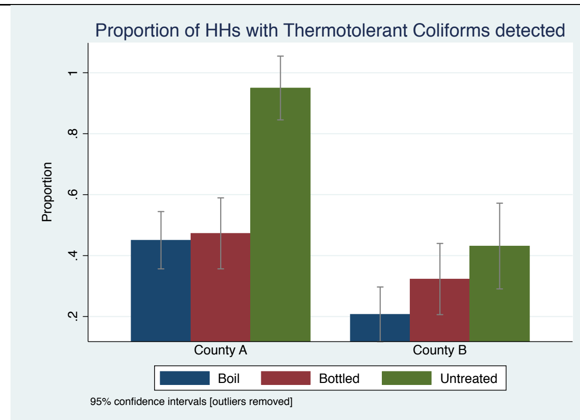

Mean number of TVs owned per household - per capita
0
.1
.2
.3
.4
.5
.6
.7
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Village Code
95% confidence intervals

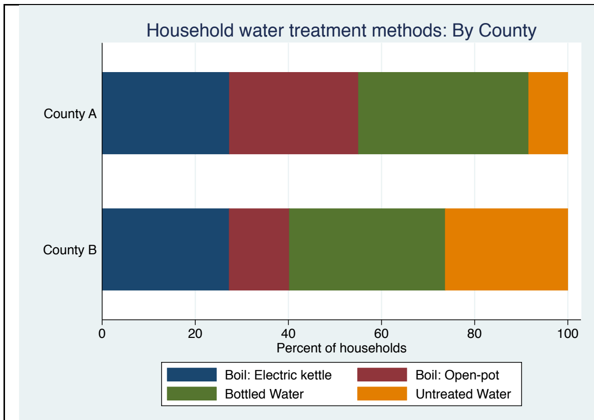

Able to pay for healthcare for serious illness/injury
percent
0
20
40
60
80
100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Village Code
No
Yes, if money is borrowed
Yes, with much difficulty
Yes, with some difficulty
Yes, b/c govt or employer helps
Yes, can afford it

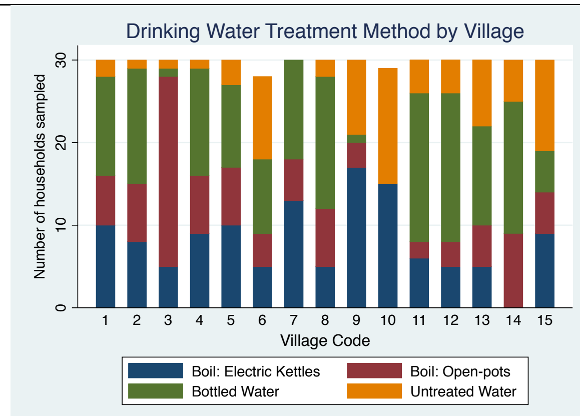

Frequency HH adults drinnk untreated water
percent
0
20
40
60
80
100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Village Code
Never
Rarely
Sometimes
Often
Always

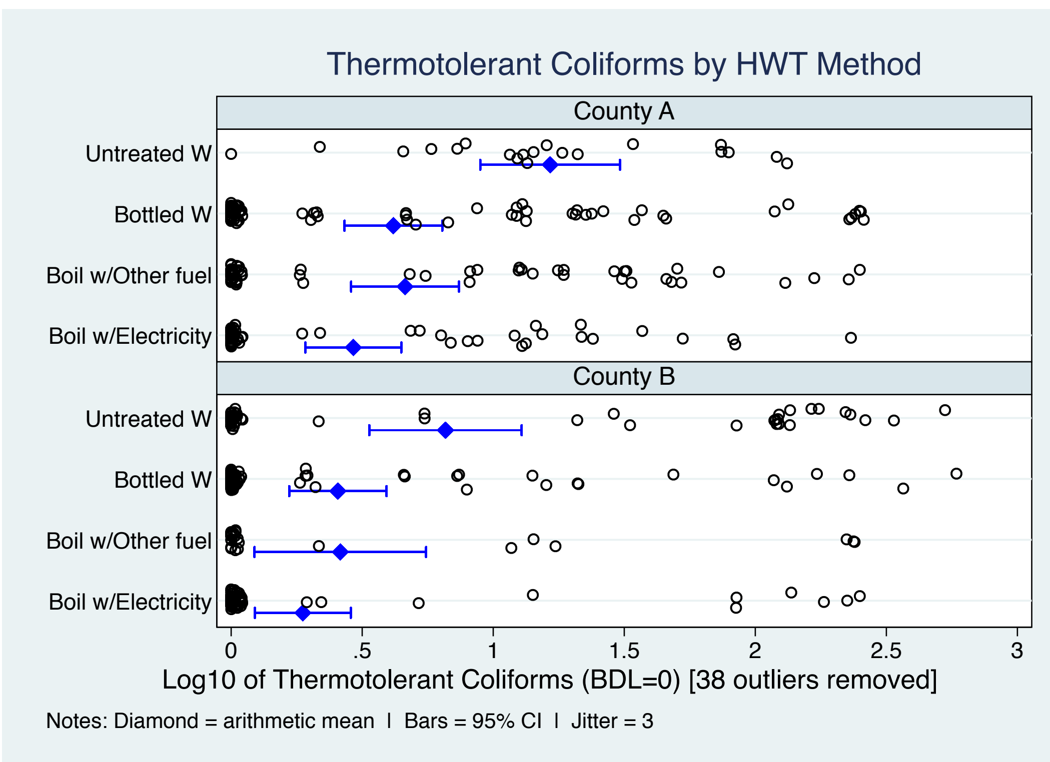

Toilet/latrine HH members usually use
percent
0
20
40
60
80
100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Village Code
None, open defecation
Open pit, communal
Enclosed pit, communal
Enclosed improved-vent pit C
Enclosed pour-flush C
Compost or biogas C
Open pit, private
Enclosed pit, private
Enclosed improved-vent pit P
Enclosed pour-flush P
Enclosed flush P
Compost or biogas P

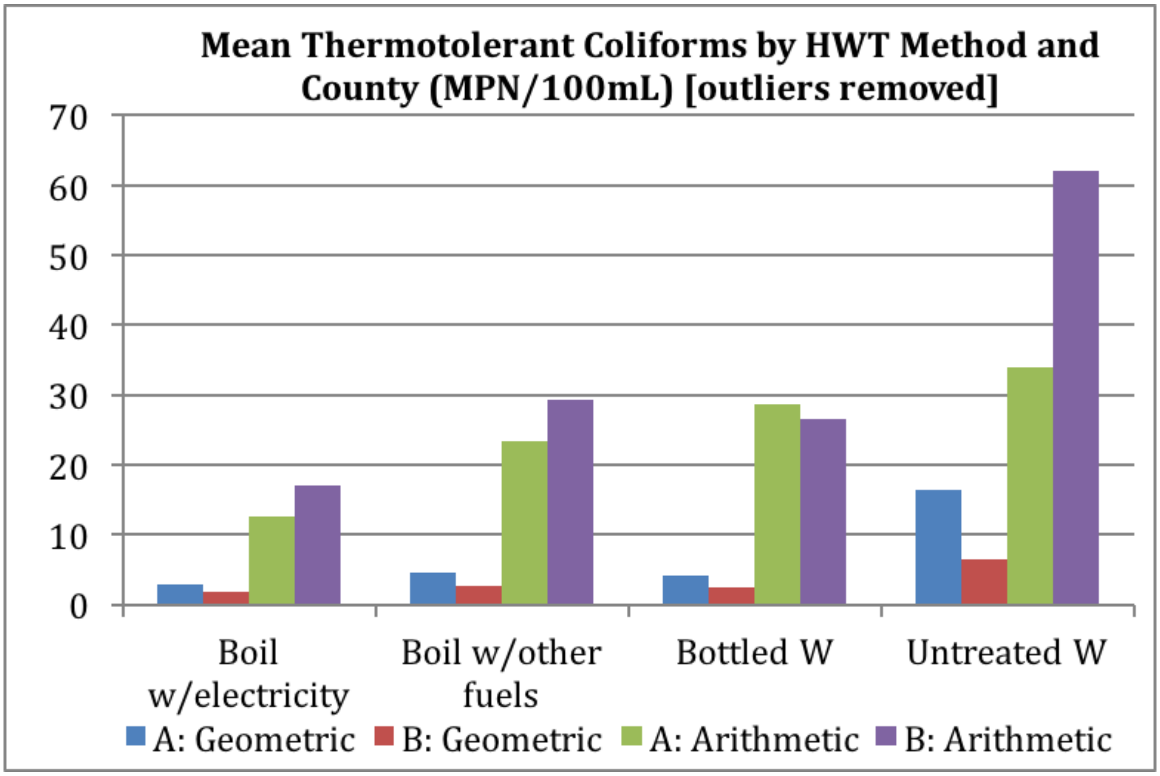

Proportion of HHs that drink boiled, bottled & untreated W
(Based on variable: BlBtUn)
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
0
20
40
60
80
100
percent
Boil
Bottled
Untreated

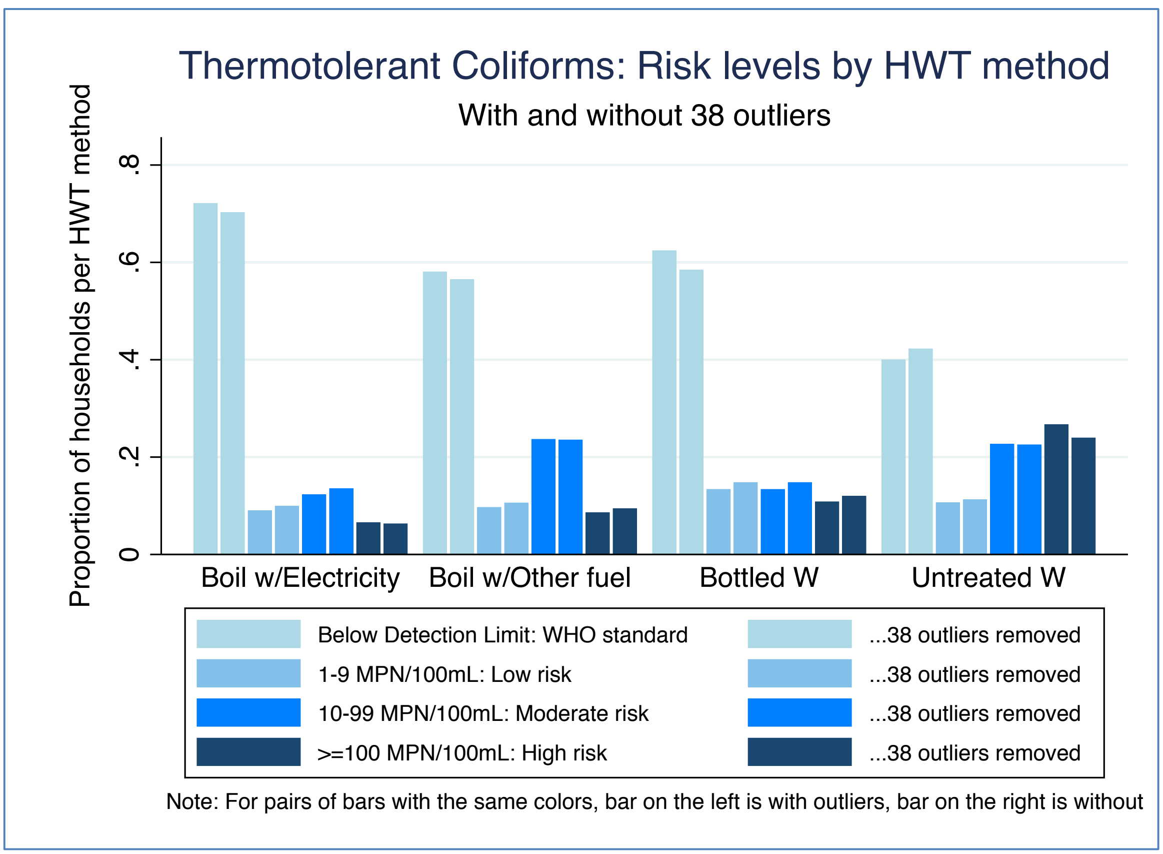

Proportion of HHs with Thermotolerant Coliforms detected
Proportion
.2
.4
.6
.8
1
County A
County B
Boil
Bottled
Untreated
95% confidence intervals [outliers removed]


Household water treatment methods: By County
County A
County B
0
20
40
60
80
100
Percent of households
Boil: Electric kettle
Boil: Open-pot
Bottled Water
Untreated Water


Drinking Water Treatment Method by Village
Number of households sampled
0
10
20
30
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Village Code
Boil: Electric Kettles
Boil: Open-pots
Bottled Water
Untreated Water


Thermotolerant Coliforms by HWT Method
County A
Untreated W
Bottled W
Boil w/Other fuel
Boil w/Electricity
County B
Untreated W
Bottled W
Boil w/Other fuel
Boil w/Electricity
0
.5
1
1.5
2
2.5
3
Log10 of Thermotolerant Coliforms (BDL=0) [38 outliers removed]
Notes: Diamond = arithmetic mean | Bars = 95% CI | Jitter = 3


Mean Thermotolerant Coliforms by HWT Method and County (MPN/100mL) [outliers removed]
70
60
50
40
30
20
10
0
Boil w/electricity
Boil w/other fuels
Bottled W
Untreated W
A: Geometric
B: Geometric
A: Arithmetic
B: Arithmetic


Thermotolerant Coliforms: Risk levels by HWT method
With and without 38 outliers
Proportion of households per HWT method
0
.2
.4
.6
.8
Boil w/Electricity
Boil w/Other fuel
Bottled W
Untreated W
Below Detection Limit: WHO standard
1-9 MPN/100mL: Low risk
10-99 MPN/100mL: Moderate risk
>=100 MPN/100mL: High risk
...38 outliers removed
...38 outliers removed
...38 outliers removed
...38 outliers removed
Note: For pairs of bars with the same colors, bar on the left is with outliers, bar on the right is without

4. Initial analysis

4.1 Misc. tests for differences between groups

Simple t-test to see if there is a difference in TTC between HH's that treat and HH's that do not treat (sample size is large enough that normality is not required). First use Variance Ratio Test (find that yes, unequal) and then use t-test for unequal variance.

```
Variance ratio test
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
Untreate |      71    54.14085    11.31407    95.33404    31.57565    76.70605
Treat DW |     332     22.9006    3.521874    64.17159    15.97252    29.82868
---------+--------------------------------------------------------------------
combined |     403    28.40447    3.562723    71.52116    21.40057    35.40836
------------------------------------------------------------------------------
    ratio = sd(Untreate) / sd(Treat DW)                           f =   2.2070
Ho: ratio = 1                                    degrees of freedom =  70, 331

    Ha: ratio < 1               Ha: ratio != 1                 Ha: ratio > 1
  Pr(F < f) = 1.0000         2*Pr(F > f) = 0.0000           Pr(F > f) = 0.0000


Two-sample t test with unequal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
Untreate |      71    54.14085    11.31407    95.33404    31.57565    76.70605
Treat DW |     332     22.9006    3.521874    64.17159    15.97252    29.82868
---------+--------------------------------------------------------------------
combined |     403    28.40447    3.562723    71.52116    21.40057    35.40836
---------+--------------------------------------------------------------------
    diff |            31.24024    11.84955                7.676348    54.80414
------------------------------------------------------------------------------
    diff = mean(Untreate) - mean(Treat DW)                        t =   2.6364
Ho: diff = 0                     Satterthwaite's degrees of freedom =  84.0559

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9950         Pr(|T| > |t|) = 0.0100          Pr(T > t) = 0.0050
```

Result: Reject null hypothesis and accept alternative hypothesis (p<.01) that the mean TTC in HHs that treat their DW is different than in HHs that do not treat (t=2.64, df=401, p=0.01).

We can also use a non-parametric test, Wilcoxon rank-sum, to examine the difference:

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

   TreatDW_D |      obs    rank sum    expected
-------------+---------------------------------
 Untreated W |       71     17368.5       14342
Treat DW (bo |      332     64037.5       67064
-------------+---------------------------------
    combined |      403       81406       81406

unadjusted variance   793590.67
adjustment for ties  -165904.65
                     ----------
adjusted variance     627686.02

Ho: TTC_or(TreatD~D==Untreated W) = TTC_or(TreatD~D==Treat DW (boil or bottled))
             z =   3.820
    Prob > |z| =   0.0001
```

Using ANOVA with the logged TTC (TTCmL10_or), we see that the means are not equal (p=0.0001), and the Bartlett's test indicates the variances are unequal. Using the Scheffe's test, there are now two mean-differences that are significant, Boiling with an electricity and Untreated (p<.001) and Bottled water and Untreated (p=0.006).

```
Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      14.0643026      3   4.68810088      7.52     0.0001
 Within groups      248.754502    399   .623444868
------------------------------------------------------------------------
    Total           262.818805    402   .653778122

Bartlett's test for equal variances:  chi2(3) =   9.3324  Prob>chi2 = 0.025

Comparison of Log10 of Thermotolerant Coliforms (BDL=0) [38 outliers removed]
             by Cat: Boil-Electric,  Boil-OF, Bottled, Untreated
                                  (Scheffe)
Row Mean-|
Col Mean |   Boil w/E   Boil w/O   Bottled
---------+--------------------------------
Boil w/O |    .219851
         |      0.300
         |
Bottled  |     .15277   -.067081
         |      0.516      0.945
         |
Untreate |    .563148    .343296    .410377
         |      0.000      0.065      0.006
```

Lastly, use a Bonferroni test (instead of the Scheffe's test) for the logged TTC data and see that now there are statistically significant difference between Untreated water and all three HWT methods (p=0.000, .044, and .002 respectively).

Comparison of Log10 of Thermotolerant Coliforms (BDL=0) [38 outliers removed]
by Cat: Boil-Electric, Boil-OF, Bottled, Untreated
(Bonferroni)

Row Mean-Col Mean	Boil w/E	Boil w/O	Bottled
Boil w/O	.219851		
	0.335		
Bottled	.15277	-.067081	
	0.788	1.000	
Untreate	.563148	.343296	.410377
	0.000	0.044	0.002

4.2 Between & within standard deviations for covariates

Given the analysis focus on multi-level modeling (MLM) and accounting for the variance between and within villages, useful to look at the overall, between, and within SD for the key variables.

TC & TTC

Variable		Mean	Std. Dev.	Min	Max	Observations
TC_or	overall	2062.88	3890.236	0	24000	N = 407
	between		1844.453	51.82609	6192.286	n = 15
	within		3449.398	-4069.406	22187.6	T-bar = 27.1333
TTC_or	overall	28.26108	71.28362	0	540	N = 406
	between		15.24542	5.178571	57.4	n = 15
	within		69.75403	-29.13892	518.6457	T-bar = 27.0667
TTCmL1~r	overall	.5642753	.8076909	0	2.732394	N = 406
	between		.1890895	.1260327	.8398298	n = 15
	within		.7860099	-.2755545	2.86727	T-bar = 27.0667

Variable		Mean	Std. Dev.	Min	Max	Observations
D_BoilE	overall	.2729306	.4459646	0	1	N = 447
	between		.1498525	0	.5666667	n = 15
	within		.4217955	-.293736	1.106264	T-bar = 29.8

D_BoilO	overall	.2080537	.4063703	0	1	N = 447
	between		.1730261	0	.7666667	n = 15
	within		.3702156	-.558613	1.141387	T-bar = 29.8
D_Bott~W	overall	.3512304	.4778897	0	1	N = 447
	between		.2031954	0	.6	n = 15
	within		.4356339	-.2487696	1.317897	T-bar = 29.8
D_Untr~d	overall	.1677852	.3740941	0	1	N = 447
	between		.149199	0	.4827586	n = 15
	within		.3454918	-.3149734	1.134452	T-bar = 29.8

Variable		Mean	Std. Dev.	Min	Max	Observations
TreatD~D	overall	.8322148	.3740941	0	1	N = 447
	between		.149199	.5172414	1	n = 15
	within		.3454918	-.1344519	1.314973	T-bar = 29.8
Boil_D	overall	.4809843	.5001981	0	1	N = 447
	between		.178565	.2666667	.9333333	n = 15
	within		.4693487	-.452349	1.214318	T-bar = 29.8

IMPROVED WATER SOURCE = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
Impr~e_D	overall	.4775785	.5000579	0	1	N = 446
	between		.3086697	0	.9333333	n = 15
	within		.4009893	-.4557549	1.444245	T-bar = 29.7333

SOAP USED (Q107) = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
SoapUs~D	overall	.4228188	.4945607	0	1	N = 447
	between		.1835842	.1333333	.7333333	n = 15
	within		.4614581	-.3105145	1.289485	T-bar = 29.8

SAFE STORAGE = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
SafeSt~D	overall	.8650602	.3420716	0	1	N = 415
	between		.1033014	.6551724	1	n = 15
	within		.3267118	-.1016064	1.209888	T-bar = 27.6667

HAND WASHING BEFORE MEALS = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
Hand~M_D	overall	.8422222	.3649382	0	1	N = 450
	between		.0912581	.6666667	1	n = 15
	within		.3541042	-.1244444	1.175556	T = 30

HAND WASHING POST DEFECATION = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
Hand~D_D	overall	.5511111	.4979344	0	1	N = 450
	between		.1547485	.3	.9	n = 15
	within		.4749087	-.3488889	1.251111	T = 30

SAFE TOILET = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
SafeTo~D	overall	.857461	.349992	0	1	N = 449
	between		.123027	.6333333	1	n = 15
	within		.3291364	-.1092056	1.224128	T-bar = 29.9333

DIARRHEA = 1

Variable		Mean	Std. Dev.	Min	Max	Observations
Diarrh~D	overall	.0380313	.1914862	0	1	N = 447
	between		.0277732	0	.1	n = 15
	within		.1895886	-.0619687	1.004698	T-bar = 29.8

HEAD OF HH AGE

Variable		Mean	Std. Dev.	Min	Max	Observations
head_h~e	overall	52.39644	12.49245	24	80	N = 449
	between		3.134994	46.83333	56.96667	n = 15
	within		12.1205	24.92977	81.5631	T-bar = 29.9333

ADULTS IN THE HH (AVERAGE)

Variable		Mean	Std. Dev.	Min	Max	Observations
HHp_a_~g	overall	3.57	1.448865	0	12	N = 450
	between		.4534349	2.933333	4.6	n = 15
	within		1.3809	.07	10.97	T = 30

CHILDREN IN THE HH

Variable		Mean	Std. Dev.	Min	Max	Observations
HHp_c_~l	overall	1.068889	1.115655	0	7	N = 450
	between		.186644	.7666667	1.333333	n = 15
	within		1.100955	-.2644444	6.902222	T = 30

NUMBER OF TVS HH OWNS

Variable		Mean	Std. Dev.	Min	Max	Observations
q71	overall	1.414254	.8031033	0	6	N = 449
	between		.2894204	1.033333	1.8	n = 15
	within		.7526261	-.3857461	6.000461	T-bar = 29.9333

MINUTES TO REACH BASIC HEALTH CENTER

Variable		Mean	Std. Dev.	Min	Max	Observations
q11	overall	11.33409	10.75531	1	80	N = 443
	between		7.249113	3.68	29.36667	n = 15
	within		8.158365	-17.03258	61.96742	T-bar = 29.5333

5. Multilevel Mixed-Effects Modeling (MLM)

Due to the nature of the sampling frame, with a constant of 30 HHs in each of 15 villages, this clustering must be accounted for because cluster-membership impacts HH characteristics; that is, HHs in one cluster are expected to be more similar to each other than to HHs in another cluster. Multilevel models allow us to examine the random error from the HHs (level-1) and villages (level-2) in our sample (rather than just the overall random error). Similarly, multilevel models allow us to disaggregate the residuals.

The models below are similar to standard ordinary least-squares regression (OLS) models in that covariates are estimated directly, but the intercepts for each cluster are not directly estimated, rather random effects estimation is used to estimate the variance between and within clusters. For this reason multilevel models are also called mixed-effects models (because of the mixing of fixed and random effects in one model).

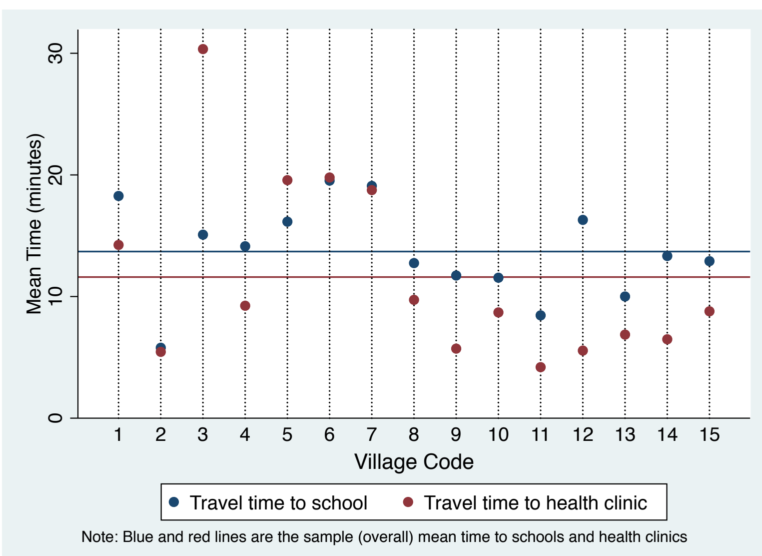
5.1 Explanation MLM purpose and notation

Note/citation: This explanation is based on Rabe-Hesketh and Skrondal (2012).

For our data, households are nested in villages that are nested within counties, with a constant of 30 households in each of 15 villages, with eight villages (1-8) in the low-income County A and seven (9-15) villages in the high-income County B.

For all the model equations below, level-1 households are represented with *i*, and level-2 villages with *j* (i.e., level-1 units *i* are clustered in level-2 units *j*). Since our units are grouped in clusters the units are not independent for the various covariates (due to this clustering effect); that is, we expect that HHs in the same villages will be more highly correlated to each other than to HHs in other villages for the covariates we are interested in (i.e., there is within-cluster dependence). Multilevel models enable us to better address and understand the unexplained variation (i.e., unobserved heterogeneity) between the HHs and villages (level-1 and level-2 residuals).

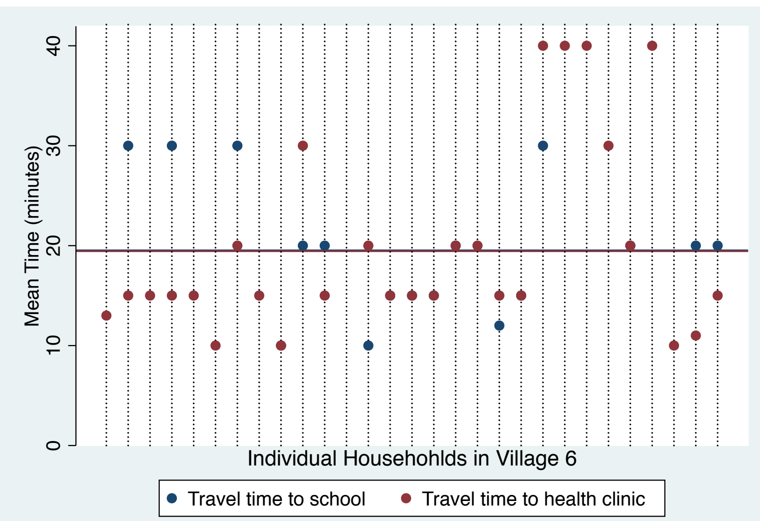
As an example of this between and within cluster variability, consider the graph below, based on data from our sample, where the mean time for school children to travel to school is plotted in blue dots and the mean travel time to reach the nearest basic health clinic is plotted in red dots for each village. In addition, the grand means are shown with two horizontal lines: blue for the school travel time and red for the travel time to the nearest health center.



The point of this graph, in addition to highlighting differences in travel times between County A and County B, is to show that there is a good deal of variation between these mean times in each village, but that, overall, the two mean times are more similar (less variance) within villages as compare to across them. That is, the village-level means vary around the grand means shown with the horizontal lines, but within a given village we expect the two means to be closer to each other than to one or the other mean from a different village.

For example, In village two there is almost no within-cluster variation, but we see that these times are well below the sample means (the horizontal lines) as compared with village six which also has very little within-cluster variation, but is above (higher than) the sample means and slightly closer (less variance) from the grand means than village two. Thus when we examine these types of relationships (i.e., correlations in access to education and access to healthcare) for our data we should calculate intercepts for each village, since these will be more accurate as far as looking at within-cluster variation (variation of each HH from the cluster mean that is) versus simply using the sample means, or using one intercept for our entire sample.

To make this perhaps even clearer, we can examine the the within-cluster variation in village six in the graph below (note that not every HH has children, so there are fewer data points which make up the estimates of average travel time of children to schools). We see that within village six the values for each HH vary considerably around the village means (which are essentially the same as we saw in the first graph (just under 20 minutes). If we do not use multilevel modeling we lose an understanding of the impact of the variation of certain covariates in each village on the whole sample.



Note: Blue and red lines are the Village Six mean time to schools and health clinics

Multilevel modeling allows us to examine the deviation/variation of each observation from its cluster mean, and in turn the deviation/variation of the cluster mean from the grand (total) mean (or even the deviation of the cluster means from county means and in turn the deviation of the county means from the grand mean).

Thus, the residual (the error term) for a given observation is broken up, disaggregated, into the variance at each of these different levels. The within SD is the square root of theta, which is the deviation of level-1 (i) observations from their cluster means (i.e., the standard deviation of the residuals for the fixed-effects portion of the model) and the between SD is the square root of psi is the deviation of level-2 (j) cluster means from the grand mean (i.e., the standard deviation of the level-2 residuals for the random-effects portion of the model). A third step would be to examine the deviation of the county means from the grand mean, but given that there are only two counties (i.e., two clusters at this third level), this is not done here (except as part of the sensitivity analyses), but for a larger study with many counties it would be worthwhile to explore a three-level model.

To be even more precise, multilevel models allow one to break down the residuals/errors into level-2 residuals, which capture the error for all units in a cluster and are denoted with zeta, and the level-1 residuals (as in OLS) that are specific to the units in the clusters, and denoted with epsilon. Using a random effects approach allows the intercept estimate to vary across clusters, which is of course appropriate because we do not expect to have the same intercept in each cluster. As such, zeta provides an understanding of how the cluster means deviate from the overall mean (i.e., the population mean estimate).

The between-cluster variance is represented using psi, which tells us, on average across our sample, what percentage of the variance is due to cluster membership. As with OLS, the level-1 residuals provide an understanding of how the observations vary/deviate from the cluster means and this within-cluster variance (i.e., the variance of *y* above and below the regression line for each cluster) is represented using theta. Put another way, we do not want to treat zeta as fixed (meaning only the level-1 residuals would vary) since we expect the intercept to vary from cluster to cluster.

Thus, the total residual error is the sum of zeta and epsilon (since they are not correlated it is appropriate to sum them in this fashion). And, similarly, the total residual variance, and the total variance of our DV, is the sum of psi and theta (i.e., the variance components).

We can use the ICC estimate of rho to better understand the degree of variance that is due to cluster membership. This is somewhat similar to the coefficient of determination (R-squared) in OLS, in that it is the proportion of total variance that is due to the clustering effect since rho is the ratio of the between-cluster variance to the between and within cluster variance (i.e., the percentage of variance explained by between-cluster effects).

A rho close to zero would suggest that cluster membership does not explain much of the variability, and actually using OLS might be more appropriate. Conversely, the larger rho is, the more that cluster-membership explains the variability.

Thus, for these models, the coefficient of determination helps us understand what proportion of the residual variance is explained by the model covariates.

5.2 REML versus MLE and Random versus Fixed effects

A last consideration is whether to use Maximum Likelihood Estimation (MLE) or Restricted Maximum Likelihood Estimation (REML). Since we have a relatively small number of clusters (15) REML will likely be a better and more conservative option (with 20+ clusters MLE would likely be the preferred option).

REML estimates psi by penalizing the estimate by one degree of freedom, since we have a relatively large sample size this is not especially significant. REML also provides less biased variance components estimates generally, as compared to MLE, and this is especially the case when the data is balanced such as ours. Indeed, that our data is balanced across clusters (i.e., a constant of 30 HHs per cluster) generally makes this and other analysis more straightforward (MLE is analyzed in the sensitivity analysis below).

Theoretically, the use of Random Effects is preferred to Fixed Effects because we are interested in the variance estimates for the population from which our sampling units (HHs) and clusters (villages) come, rather than sample-specific estimates for the clusters that we happened to randomly select. That is, the inferences we wish to make are about the population from which our sample is taken, so using random effects will allow us to estimate the mean/average coefficient values and and variance psi for the population from which our random sample was taken. Random effects requires having at least 10 clusters, so for our sample this criteria is met.

In order to formally test whether random or fixed effects would be most appropriate I used the Hausman specification test using the variables: ICC_D, Boil_C, and TreatDW_D as predictors of TTCmL10_or. The resulting p-values were .8018, .9164, and .1252. Since none were less than .05 this indicates that there is not a sufficiently significant difference in the estimated coefficients when using a fixed effects, as compared to random effects, and therefore there is no problem with using Random Effects.

5.3 Null model and simple random intercept models to examine potential confounding and intermediate modifier effects

5.3.1 Null Model

The first model is a null/unconditional Variance Components model (aka, a Random Intercept Model) which we use to understand the potential impact of clustering on the outcomes of drinking water quality (as measured via *TTCmL10_or*).

```
Mixed-effects REML regression                   Number of obs      =       406
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        22
                                                               avg =      27.1
```

```
                                                         max =         30
                                           Wald chi2(0)       =          .
Log restricted-likelihood = -490.30728         Prob > chi2        =          .
------------------------------------------------------------------------------
  TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |    .565115   .0499436    11.32   0.000     .4672274    .6630026
------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons) |   .1170737   .0594498      .0432734    .3167363
-----------------------------+------------------------------------------------
               sd(Residual) |   .7996255    .028572      .7455413    .8576331
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     1.74 Prob >= chibar2 = 0.0939
```

The Likelihood Ratio (LR) test shown at the bottom of the output is essentially testing the hypothesis that the between-level intercept variance ($.1170737^2$) is zero, which would mean that there is no random intercept in the model, and therefore a multi-level model is not necessary, and OLS could be used instead. While the p-value for the LR test =.0939 for this simple model, this is not the case for the full models below or much of the between and within SD data presented above for key variables, all of which indicates that clustering should be accounted for in our regression models. Thus, for this model we will ignore the non-significant LR test result.

5.3.2 Model One: Binary for treat/don't treat drinking water (TreatDW_D)

Before running a model that controls for other factors known to be related to drinking water quality, to establish the effectiveness (or not) of drinking water treatment in isolation of other variables, we will first analyze the impact of drinking water treatment by itself on resulting water quality, taking into account the impact of clustering (again, why we are using multi-level models in the first place).

Thus, we add the variable TreatDW_D to the random intercept model (essentially, we are just adding a covariate to the Variance Components model).

```
Mixed-effects REML regression                  Number of obs      =        403
Group variable: aa3                            Number of groups   =         15
                                               Obs per group: min =         22
                                                              avg =       26.9
                                                              max =         30

                                               Wald chi2(1)       =      20.83
```

```
Log restricted-likelihood = -478.36812          Prob > chi2       =    0.0000
------------------------------------------------------------------------------
  TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   TreatDW_D |  -.4806361   .1053149    -4.56   0.000    -.6870496   -.2742226
       _cons |   .9638668   .1025876     9.40   0.000     .7627987    1.164935
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1475505   .0565998      .0695702    .3129379
-----------------------------+------------------------------------------------
                sd(Residual) |    .778618   .0279715      .7256805    .8354172
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     3.94 Prob >= chibar2 = 0.0235
```

The total variance is $.1475505^2 + .778618^2 = 0.62801714$, meaning the Coefficient of Determination (aka, R^2) = 0.038416437. This is calculated by taking the difference in total variance between this model and the Null model and dividing that by the Null model total variance).

Note: This method of calculating R^2 is repeated for all relevant models below (for more information see: Rabe-Hesketh and Skrondal, 2012: 136).

The likelihood-ratio test result suggests that using this type of random effects model is superior to using a fixed effects model (p=0.0235).

As expected, we see that if HHs do treat their drinking water (by any method, boiling or bottled water) there is a nearly half-log reduction (-.481) in the TTC detected in their drinking water, as compared to HHs that do not treat their drinking water.

5.3.3 Model Two: HWT disaggregated into dummy variables (D_BoilE, D_BoilO, D_BottledW)

D_BoilE	Boil with electric kettles =	1, 0, 0
D_BoilO	Boil with pots =	0, 1, 0
D_BottledW	Bottled Water =	0, 0, 1
	Untreated Water =	0, 0, 0

```
mixed TTCmL10_or D_BoilE D_BoilO D_BottledW || aa3:, reml stddeviations
Mixed-effects REML regression                   Number of obs      =       403
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        22
                                                               avg =      26.9
                                                               max =        30
                                                Wald chi2(3)       =     23.56
```

```
Log restricted-likelihood = -479.64495          Prob > chi2        =    0.0000
------------------------------------------------------------------------------
  TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     D_BoilE |  -.5711408   .1208128    -4.73   0.000    -.8079295   -.3343522
     D_BoilO |  -.3759711   .1311717    -2.87   0.004    -.6330629   -.1188793
  D_BottledW |  -.4480329    .117999    -3.80   0.000    -.6793067   -.2167592
       _cons |    .955028   .1011725     9.44   0.000     .7567335    1.153322
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1341315   .0575054      .0578896    .3107858
-----------------------------+------------------------------------------------
                sd(Residual) |   .7789755    .028051      .7258919     .835941
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     2.82 Prob >= chibar2 = 0.0466
```

5.3.4 Model Two: HWT disaggregated into dummy variables – Logistic comparison

Given the central importance of HWT method on TTC, this section provides the results of a multi-level logistic regression where the DV is a binary such that if TTC was detected (at any level) the DV=1 and if TTC were BDL the DV=0. This is done in order to further establish the clinical and statistical significance of these three HWT methods on associated TTC in water samples.

```
Mixed-effects logistic regression               Number of obs      =       403
Group variable:             aa3                 Number of groups   =        15
                                                Obs per group: min =        22
                                                               avg =      26.9
                                                               max =        30
Integration method: mvaghermite                 Integration points =        15
                                                Wald chi2(3)       =     17.87
Log likelihood = -257.29953                     Prob > chi2        =    0.0005
-------------------------------------------------------------------------------
TTC_cont_D_or | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      D_BoilE |   .2262284   .0805262    -4.18   0.000     .1126059    .4544992
      D_BoilO |   .3930956   .1498025    -2.45   0.014     .1862596    .8296169
   D_BottledW |   .3365644   .1170739    -3.13   0.002     .1702072     .665516
        _cons |   1.766447   .5671971     1.77   0.076     .9414212    3.314493
--------------+----------------------------------------------------------------
aa3           |
    var(_cons)|   .4208473   .2399356                      .1376681    1.286518
-------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    14.42 Prob>=chibar2 = 0.0001
```

5.3.5 Model Three: Binary for Improved/unimproved water source (ImprovedSource_D)

```
Mixed-effects REML regression                   Number of obs      =       403
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        20
                                                               avg =      26.9
                                                               max =        30
                                                Wald chi2(1)       =      0.85
Log restricted-likelihood = -486.70197          Prob > chi2        =    0.3555
----------------------------------------------------------------------------------
      TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
ImprovedSource_D |  -.0805945     .08722    -0.92   0.355    -.2515426    .0903536
           _cons |   .5961484   .0669599     8.90   0.000     .4649093    .7273874
----------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1342122   .0595819      .0562226    .3203855
-----------------------------+------------------------------------------------
                sd(Residual) |   .7960512    .028602      .7419206    .8541311
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     2.57 Prob >= chibar2 = 0.0546
```

5.3.6 Model Four: Binary for Safe/unsafe water storage (SafeStorage_D)

```
Mixed-effects REML regression                   Number of obs      =       373
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        18
                                                               avg =      24.9
                                                               max =        29
                                                Wald chi2(1)       =      0.50
Log restricted-likelihood = -449.80316          Prob > chi2        =    0.4814
-------------------------------------------------------------------------------
   TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
SafeStorage_D |  -.0847005   .1202959    -0.70   0.481    -.3204761    .1510751
        _cons |   .6322421   .1166831     5.42   0.000     .4035474    .8609367
-------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
```

```
aa3: Identity                |
                   sd(_cons) |    .135838   .0606896      .0565877    .3260772
-----------------------------+------------------------------------------------
                sd(Residual) |   .7946417   .0297153      .7384838      .85507
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     2.48 Prob >= chibar2 = 0.0575
```

5.3.7 Model Five: HWT methods and method of water storage

```
Mixed-effects REML regression                   Number of obs      =       370
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        18
                                                               avg =      24.7
                                                               max =        29
                                                Wald chi2(4)       =     22.07
Log restricted-likelihood = -439.90884          Prob > chi2        =    0.0002
------------------------------------------------------------------------------
   TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      D_BoilE |  -.5752846   .1260358    -4.56   0.000    -.8223103   -.3282589
      D_BoilO |  -.3618174   .1365446    -2.65   0.008    -.6294399    -.094195
   D_BottledW |  -.4211957   .1213235    -3.47   0.001    -.6589854   -.1834059
SafeStorage_D |  -.0891033   .1201661    -0.74   0.458    -.3246245    .1464179
        _cons |   1.010186   .1508459     6.70   0.000     .7145334    1.305838
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |    .153245   .0589823      .0720723      .32584
-----------------------------+------------------------------------------------
                sd(Residual) |   .7741238   .0291836      .7189871    .8334888
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     3.91 Prob >= chibar2 = 0.0241
```

5.3.8 Model Six: Water source and method of water storage

```
Mixed-effects REML regression                   Number of obs      =       371
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.7
                                                               max =        29
                                                Wald chi2(2)       =      0.98
Log restricted-likelihood =  -447.4892          Prob > chi2        =    0.6125
------------------------------------------------------------------------------
      TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
------------------+----------------------------------------------------------------
ImprovedSource_D |  -.0823123   .0922254    -0.89   0.372    -.2630708    .0984461
   SafeStorage_D |  -.0511074   .1211026    -0.42   0.673    -.2884642    .1862493
           _cons |   .6373717   .1269131     5.02   0.000     .3886266    .8861167
------------------------------------------------------------------------------------
```

```
------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1567049     .06172      .0724148     .339108
-----------------------------+------------------------------------------------
                sd(Residual) |   .7907605   .0297103      .7346218    .8511893
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     3.69 Prob >= chibar2 = 0.0274
```

5.3.9 Model Seven: HWT methods, water source and method of water storage

```
Mixed-effects REML regression                   Number of obs      =       368
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.5
                                                               max =        29
                                                Wald chi2(5)       =     22.19
Log restricted-likelihood = -437.77903          Prob > chi2        =    0.0005
------------------------------------------------------------------------------------
      TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
         D_BoilE |  -.5673749   .1272401    -4.46   0.000    -.8167609   -.3179888
         D_BoilO |  -.3715957    .138097    -2.69   0.007    -.6422609   -.1009306
      D_BottledW |  -.4322007   .1229206    -3.52   0.000    -.6731207   -.1912807
ImprovedSource_D |   -.068815   .0946747    -0.73   0.467    -.2543739     .116744
   SafeStorage_D |  -.0548742   .1209598    -0.45   0.650    -.2919511    .1822027
           _cons |   1.013584   .1594673     6.36   0.000     .7010334    1.326134
------------------------------------------------------------------------------------
```

```
------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1722106   .0617965      .0852339    .3479422
-----------------------------+------------------------------------------------
                sd(Residual) |   .7708057   .0292116      .7156267    .8302393
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     5.09 Prob >= chibar2 = 0.0121
```

5.4 Random Intercept models with multiple covariates/controls: Iterative development based on conceptual hierarchical framework

5.4.1 Model Eight: Model Seven plus Block One (Socioeconomic/HH Characteristics)

```
Mixed-effects REML regression                   Number of obs      =       362
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.1
                                                               max =        28
                                                Wald chi2(9)       =     34.85
Log restricted-likelihood = -432.41754          Prob > chi2        =    0.0001
------------------------------------------------------------------------------------
      TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
         D_BoilE |   -.607173   .1258888    -4.82   0.000    -.8539106   -.3604355
         D_BoilO |  -.4472851   .1383488    -3.23   0.001    -.7184437   -.1761265
     D_BottledW |   -.439645   .1227847    -3.58   0.000    -.6802986   -.1989913
ImprovedSource_D |  -.0355321   .0938128    -0.38   0.705    -.2194017    .1483375
   SafeStorage_D |  -.0768636   .1196038    -0.64   0.520    -.3112828    .1575555
      Literacy_D |  -.2118684   .0930891    -2.28   0.023    -.3943196   -.0294172
     head_hh_age |   .0033473   .0034812     0.96   0.336    -.0034758    .0101704
  HHp_total_in_o |  -.0028086   .0189468    -0.15   0.882    -.0399436    .0343264
        TVperCap |   -.375496   .2047053    -1.83   0.067    -.7767109     .025719
           _cons |   1.149972   .2712692     4.24   0.000     .6182938     1.68165
------------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons)  |   .1620733   .0596239      .0788079    .3333139
-----------------------------+------------------------------------------------
               sd(Residual)  |   .7578581   .0290952      .7029252     .817084
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.58 Prob >= chibar2 = 0.0162
```

Model Eight – version two (with HH population removed)

```
Mixed-effects REML regression                   Number of obs      =       362
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.1
                                                               max =        28
                                                Wald chi2(8)       =     34.93
```

```
Log restricted-likelihood = -429.38066          Prob > chi2        =    0.0000
--------------------------------------------------------------------------------
      TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+--------------------------------------------------------------
         D_BoilE |  -.6079429   .1256075    -4.84   0.000    -.8541291   -.3617566
         D_BoilO |  -.4457407   .1377673    -3.24   0.001    -.7157596   -.1757218
      D_BottledW |   -.440182   .1225657    -3.59   0.000    -.6804065   -.1999576
ImprovedSource_D |  -.0352182   .0936621    -0.38   0.707    -.2187927    .1483562
   SafeStorage_D |   -.077489    .119361    -0.65   0.516    -.3114323    .1564543
      Literacy_D |  -.2123065   .0929111    -2.29   0.022    -.3944089    -.030204
     head_hh_age |   .0032201   .0033684     0.96   0.339    -.0033819    .0098221
        TVperCap |   -.363942     .18897    -1.93   0.054    -.7343165    .0064324
           _cons |    1.13839   .2594705     4.39   0.000     .6298368    1.646942
--------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1619275   .0595087      .0787956    .3327661
-----------------------------+------------------------------------------------
                sd(Residual) |   .7568002   .0290137      .7020182    .8158571
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.60 Prob >= chibar2 = 0.0160
```

5.4.2 Model Nine: Model 8.2 plus Block Two (Healthcare, Bottled water, Sanitation)

```
Mixed-effects REML regression                   Number of obs      =       355
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        16
                                                               avg =      23.7
                                                               max =        28
                                                Wald chi2(11)      =     36.11
Log restricted-likelihood = -426.47574          Prob > chi2        =    0.0002
----------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+--------------------------------------------------------------
           D_BoilE |  -.6162756    .128478    -4.80   0.000    -.8680879   -.3644633
           D_BoilO |  -.4378482    .140979    -3.11   0.002     -.714162   -.1615344
        D_BottledW |   -.454487   .1273246    -3.57   0.000    -.7040387   -.2049353
  ImprovedSource_D |  -.0544611   .0985059    -0.55   0.580    -.2475292     .138607
     SafeStorage_D |  -.0843224   .1219995    -0.69   0.489     -.323437    .1547921
        Literacy_D |   -.202732   .0974078    -2.08   0.037    -.3936478   -.0118162
       head_hh_age |   .0037753   .0034202     1.10   0.270    -.0029283    .0104788
          TVperCap |  -.3626332   .1924413    -1.88   0.060    -.7398112    .0145448
 BasicHealthAccess |  -.0026212   .0046838    -0.56   0.576    -.0118013    .0065588
RMBvillageBottle_r |   .5824317   .7096955     0.82   0.412    -.8085458    1.973409
      SafeToilet_D |  -.0328125   .1176106    -0.28   0.780    -.2633251    .1977001
```

```
           _cons |   .9522736   .4062173     2.34   0.019     .1561024    1.748445
------------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons) |   .1668208   .0622855      .0802489     .346786
-----------------------------+------------------------------------------------
               sd(Residual) |   .7599565   .0295103      .7042636    .8200535
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.56 Prob >= chibar2 = 0.0164
```

Model Nine – version two (with access to healthcare and type of toilet removed)

```
Mixed-effects REML regression                   Number of obs      =       362
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.1
                                                               max =        28
                                                Wald chi2(9)       =     35.56
Log restricted-likelihood = -428.49782          Prob > chi2        =    0.0000
------------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
           D_BoilE |   -.621261   .1267596    -4.90   0.000    -.8697052   -.3728169
           D_BoilO |  -.4607881   .1391875    -3.31   0.001    -.7335906   -.1879855
        D_BottledW |  -.4600095   .1250514    -3.68   0.000    -.7051057   -.2149133
  ImprovedSource_D |  -.0540946   .0966138    -0.56   0.576    -.2434542    .1352651
     SafeStorage_D |  -.0671263   .1200398    -0.56   0.576    -.3024001    .1681474
        Literacy_D |  -.1927001   .0958919    -2.01   0.044    -.3806448   -.0047553
       head_hh_age |   .0033509   .0033726     0.99   0.320    -.0032593     .009961
          TVperCap |  -.3525932   .1896733    -1.86   0.063     -.724346    .0191596
RMBvillageBottle_r |    .563613   .6977485     0.81   0.419    -.8039489    1.931175
             _cons |   .9053341   .3871578     2.34   0.019     .1465187     1.66415
------------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons) |   .1660901   .0612443      .0806252    .3421502
-----------------------------+------------------------------------------------
               sd(Residual) |   .7567969   .0290168      .7020094    .8158603
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.75 Prob >= chibar2 = 0.0147
```

5.4.3 Model Ten: Model 9.2 plus Block Three (Hand washing & soap)

```
Mixed-effects REML regression                   Number of obs      =       359
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        15
                                                               avg =      23.9
                                                               max =        28
                                                Wald chi2(12)      =     38.67
Log restricted-likelihood =   -428.075          Prob > chi2        =    0.0001
------------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
           D_BoilE |  -.5987932   .1276179    -4.69   0.000    -.8489197   -.3486668
           D_BoilO |  -.4383464   .1403701    -3.12   0.002    -.7134667    -.163226
        D_BottledW |   -.447805   .1259883    -3.55   0.000    -.6947375   -.2008726
  ImprovedSource_D |  -.0398377   .0981942    -0.41   0.685    -.2322949    .1526194
     SafeStorage_D |  -.0486265   .1228758    -0.40   0.692    -.2894586    .1922057
        Literacy_D |  -.1650583    .098309    -1.68   0.093    -.3577404    .0276237
       head_hh_age |   .0036308   .0033916     1.07   0.284    -.0030166    .0102781
         TVperCap |  -.3394143   .1908871    -1.78   0.075    -.7135461    .0347175
RMBvillageBottle_r |   .7290115   .7151657     1.02   0.308    -.6726874    2.130711
      HandwashPD_D |   .0717091   .0943302     0.76   0.447    -.1131747     .256593
        SoapUsed_D |   -.061587   .0866182    -0.71   0.477    -.2313555    .1081816
      HandwashBM_D |  -.2007147   .1276428    -1.57   0.116    -.4508899    .0494605
             _cons |   .9226568   .4036509     2.29   0.022     .1315157    1.713798
------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1667119   .0618619      .0805584    .3450026
-----------------------------+------------------------------------------------
                sd(Residual) |   .7575764   .0293009      .7022704    .8172379
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.66 Prob >= chibar2 = 0.0154
```

5.4.4 Model Eleven: Full model (all variables - for comparison)

```
Mixed-effects REML regression                   Number of obs      =       352
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        15
                                                               avg =      23.5
                                                               max =        28
                                                Wald chi2(15)      =     38.87
Log restricted-likelihood =  -429.0694          Prob > chi2        =    0.0007
------------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
           D_BoilE |  -.5977578   .1294919    -4.62   0.000    -.8515572   -.3439585
```

```
          D_BoilO |  -.4256507   .1426562    -2.98   0.003    -.7052517  -.1460497
        D_BottledW |  -.4474044    .128295    -3.49   0.000     -.698858  -.1959508
  ImprovedSource_D |  -.0391873   .1004165    -0.39   0.696    -.2360001   .1576254
     SafeStorage_D |  -.0554971   .1251436    -0.44   0.657     -.300774   .1897799
        Literacy_D |  -.1692892   .1000375    -1.69   0.091    -.3653591   .0267807
       head_hh_age |    .004306   .0035658     1.21   0.227    -.0026828   .0112949
    HHp_total_in_o |  -.0028181   .0193217    -0.15   0.884    -.0406879   .0350517
          TVperCap |  -.3553515   .2097196    -1.69   0.090    -.7663943   .0556913
 BasicHealthAccess |  -.0011901   .0048444    -0.25   0.806    -.0106849   .0083048
RMBvillageBottle_r |   .7151789   .7309493     0.98   0.328    -.7174553   2.147813
      SafeToilet_D |  -.0095541   .1228011    -0.08   0.938    -.2502398   .2311316
      HandwashPD_D |   .0825754   .0962581     0.86   0.391    -.1060871   .2712379
        SoapUsed_D |  -.0382161   .0897275    -0.43   0.670    -.2140788   .1376466
      HandwashBM_D |  -.2146599   .1309288    -1.64   0.101    -.4712756   .0419557
             _cons |    .939012   .4266379     2.20   0.028      .102817   1.775207
------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1690994   .0630878      .0813907    .3513252
-----------------------------+------------------------------------------------
                sd(Residual) |    .762033   .0299026      .7056222    .8229536
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.58 Prob >= chibar2 = 0.0162
```

Model Eleven – version two (without covariates with p>.5 but keeping Source and Storage) [note: same as Model Ten except Soap removed]

```
Mixed-effects REML regression                   Number of obs      =       362
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        17
                                                               avg =      24.1
                                                               max =        28
                                                Wald chi2(11)      =     37.95
Log restricted-likelihood = -430.00648          Prob > chi2        =    0.0001
------------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
           D_BoilE |  -.6059088   .1271302    -4.77   0.000    -.8550793  -.3567382
           D_BoilO |  -.4551329   .1394643    -3.26   0.001    -.7284778   -.181788
        D_BottledW |  -.4548118   .1252285    -3.63   0.000    -.7002552  -.2093684
  ImprovedSource_D |   -.038998   .0972361    -0.40   0.688    -.2295772   .1515812
     SafeStorage_D |  -.0467764   .1224211    -0.38   0.702    -.2867173   .1931644
        Literacy_D |  -.1701113   .0975915    -1.74   0.081    -.3613872   .0211646
       head_hh_age |   .0035887   .0033766     1.06   0.288    -.0030294   .0102068
          TVperCap |  -.3371832   .1898683    -1.78   0.076    -.7093181   .0349518
RMBvillageBottle_r |    .673637    .706143     0.95   0.340    -.7103778   2.057652
      HandwashPD_D |   .0802339   .0925418     0.87   0.386    -.1011447   .2616125
      HandwashBM_D |  -.1887674   .1261382    -1.50   0.135    -.4359936   .0584589
```

```
           _cons |   .9138504   .4002472     2.28   0.022     .1293803     1.69832
------------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons) |   .1680299   .0615476      .0819597    .3444871
-----------------------------+------------------------------------------------
               sd(Residual) |   .7562398   .0290799      .7013392    .8154381
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.86 Prob >= chibar2 = 0.0137
```

5.4.5 Model Twelve: Full model without HWT covariates

```
Mixed-effects REML regression                   Number of obs      =       362
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        15
                                                               avg =      24.1
                                                               max =        28
                                                Wald chi2(9)       =     14.91
Log restricted-likelihood = -438.77545          Prob > chi2        =    0.0935
------------------------------------------------------------------------------------
        TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
  ImprovedSource_D |  -.0531909    .097251    -0.55   0.584    -.2437992    .1374175
     SafeStorage_D |  -.0519338   .1232625    -0.42   0.674    -.2935239    .1896563
        Literacy_D |   -.163458     .09939    -1.64   0.100    -.3582588    .0313428
       head_hh_age |   .0040045    .003424     1.17   0.242    -.0027065    .0107154
          TVperCap |  -.2680525   .1953214    -1.37   0.170    -.6508754    .1147704
RMBvillageBottle_r |   .2690563   .7226671     0.37   0.710    -1.147345    1.685458
      HandwashPD_D |   .0717962   .0955899     0.75   0.453    -.1155566    .2591491
        SoapUsed_D |  -.0978916   .0877931    -1.12   0.265    -.2699629    .0741796
      HandwashBM_D |  -.2456279   .1301216    -1.89   0.059    -.5006615    .0094057
             _cons |   .7155508   .4074911     1.76   0.079    -.0831172    1.514219
------------------------------------------------------------------------------------


------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                  sd(_cons) |    .171432   .0635222      .0829257     .354401
-----------------------------+------------------------------------------------
               sd(Residual) |   .7783297   .0298597      .7219519    .8391102
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.68 Prob >= chibar2 = 0.0153
```

5.5 Model Ten: Sensitivity Analysis

The full model outputs are not presented in the interests of conserving space, but detailed summaries of each model are presented in the tables in section six below.

5.6 Model Ten: Diagnostics and results

5.6.1 Model Ten: The final model

```
Mixed-effects REML regression                   Number of obs      =       359
Group variable: aa3                             Number of groups   =        15
                                                Obs per group: min =        15
                                                               avg =      23.9
                                                               max =        28
                                                Wald chi2(12)      =     38.67
Log restricted-likelihood =   -428.075          Prob > chi2        =    0.0001
------------------------------------------------------------------------------------
       TTCmL10_or |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
          D_BoilE |  -.5987932   .1276179    -4.69   0.000    -.8489197   -.3486668
          D_BoilO |  -.4383464   .1403701    -3.12   0.002    -.7134667    -.163226
      D_BottledW |   -.447805   .1259883    -3.55   0.000    -.6947375   -.2008726
 ImprovedSource_D |  -.0398377   .0981942    -0.41   0.685    -.2322949    .1526194
    SafeStorage_D |  -.0486265   .1228758    -0.40   0.692    -.2894586    .1922057
       Literacy_D |  -.1650583    .098309    -1.68   0.093    -.3577404    .0276237
      head_hh_age |   .0036308   .0033916     1.07   0.284    -.0030166    .0102781
         TVperCap |  -.3394143   .1908871    -1.78   0.075    -.7135461    .0347175
RMBvillageBottle_r |   .7290115   .7151657     1.02   0.308    -.6726874    2.130711
     HandwashPD_D |   .0717091   .0943302     0.76   0.447    -.1131747     .256593
       SoapUsed_D |   -.061587   .0866182    -0.71   0.477    -.2313555    .1081816
     HandwashBM_D |  -.2007147   .1276428    -1.57   0.116    -.4508899    .0494605
            _cons |   .9226568   .4036509     2.29   0.022     .1315157    1.713798
------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
aa3: Identity                |
                   sd(_cons) |   .1667119   .0618619      .0805584    .3450026
-----------------------------+------------------------------------------------
                sd(Residual) |   .7575764   .0293009      .7022704    .8172379
------------------------------------------------------------------------------
LR test vs. linear regression: chibar2(01) =     4.66 Prob >= chibar2 = 0.0154
```

5.6.2 Hausman endogeneity test

One of the assumptions underlying the use of random-effects (mixed effects) models is that the random intercepts (from the villages in our case) are not correlated with any of the covariates. We can use a Hausman test to compare the OLS (fixed effects) with the MLM (random effects), denoted as "b" and "B" respectively in the output below, to see if the models are essentially the same or not.

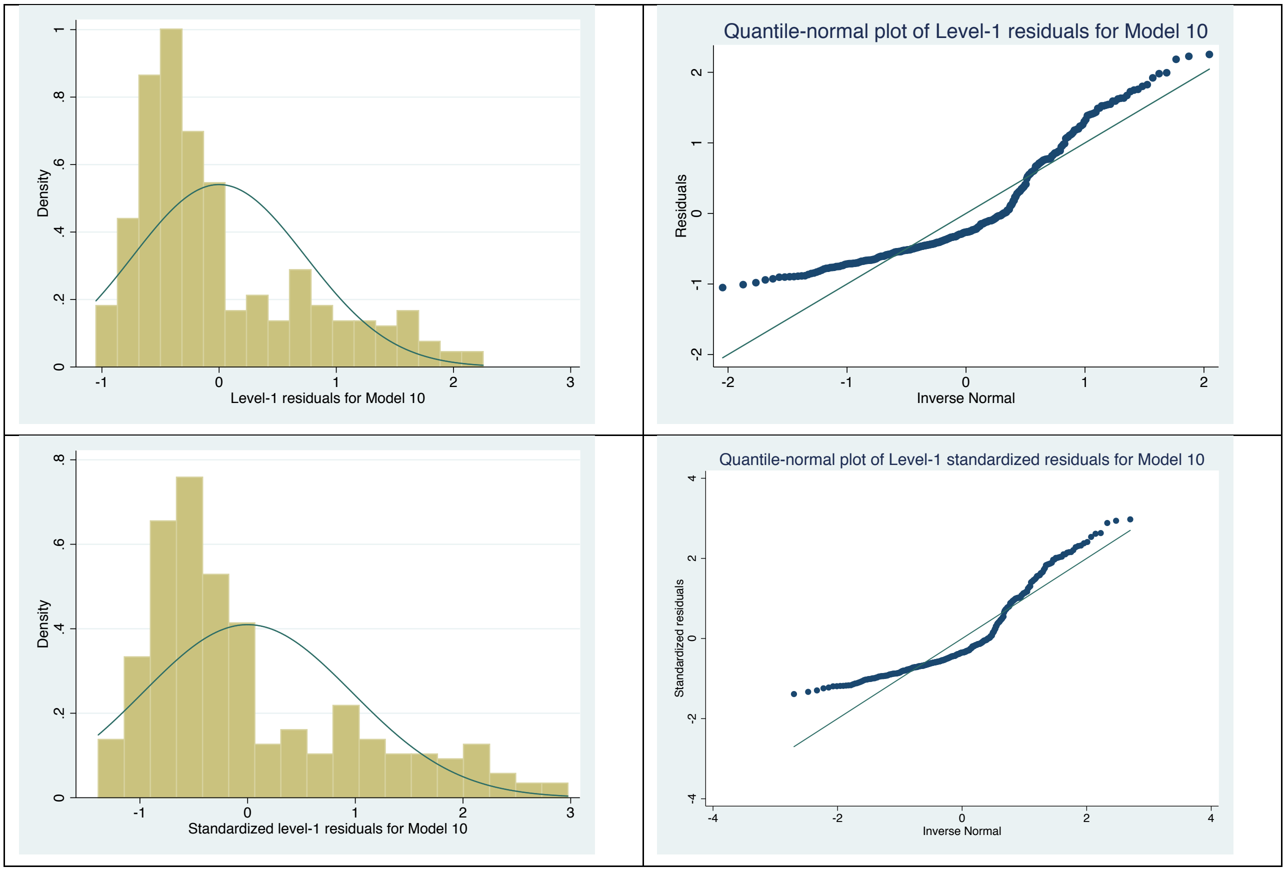
Note: For this test we use the "xtreg" command in Stata (as opposed to the "mixed" command) so the coefficient estimates are slightly different than those from the models above, but since the purpose of this test is to compare fixed versus random effects this is not a consequential difference.

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |  M10_FE_hau~n M10_RE_hau~n    Difference          S.E.
-------------+----------------------------------------------------------------
     D_BoilE |   -.5849312    -.5958211        .0108899        .0227628
     D_BoilO |   -.4167064    -.4336188        .0169125        .0366346
  D_BottledW |   -.4481497    -.4477966       -.000353         .0405023
Improved~e_D |   -.0588372    -.0432254       -.0156118        .0555399
SafeStorag~D |   -.0217266    -.0424956        .020769         .0283801
  Literacy_D |   -.1406314    -.1597226        .0190912        .0240657
 head_hh_age |    .0046018     .003855         .0007467        .0006859
    TVperCap |   -.3769606    -.3495829       -.0273777        .0375992
HandwashPD_D |    .095084      .0769159        .0181681        .0221182
  SoapUsed_D |   -.0570834    -.0603559        .0032725        .0176092
HandwashBM_D |   -.2038202    -.2014206       -.0023995        .0242524
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        3.41
                Prob>chi2 =      0.9842
```

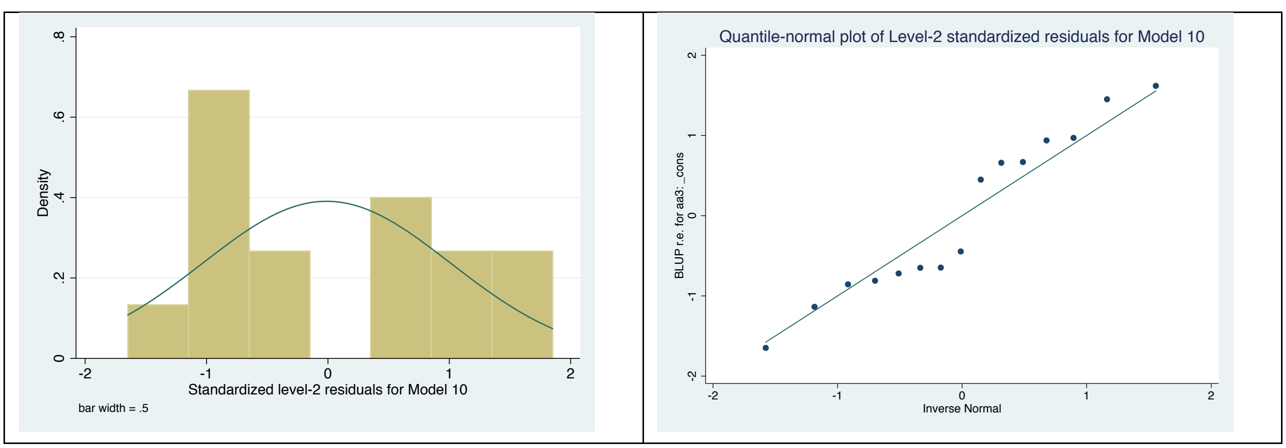
If the Hausman test statistic were significant ($p<.05$) this would suggest that the fixed-effects model is just as good if not better than the random-effects model (since only within-level information is needed). However, since the p-value = .98 this provides additional evidence (in addition to the section above on Random-effects versus Fixed-effects) that indeed a multi-level model is called for due to the importance of cluster-induced variance.

5.6.3 Distribution of residuals and normality assumptions

As discussed earlier, the model residuals do not need to be normally distributed (Rabe-Hesketh and Skrondal, 2012: 160), but it is still informative to visually examine them, expecting a skewed distribution which reflects the skewed distribution in our DV (and of this sort of water quality data generally).



When we examine the standardized residuals we see that none are +-4 SD units, so there are no extreme/outlier cases (i.e., no extreme/outlier HHs).



Since we are using multi-level models we can also visually examine the level-2 residuals. As before, we see that none of the standardized level-2 residuals are +-4 SD units, so again there are outliers to be concerned with (i.e., no outlier villages).

6. Summary tables of models

6.1 Complete summaries of all primary models

	Null Model	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Fixed Part					
Treat drinking W (vs. no)		-.48(.11)***			
Boil: E. Kettles			-.57(.12)***		
Boil: Pots			-.38(.13)**		
Drink bottled W			-.45(.12)***		
Improved W source				-.08(.09)	
Safe W storage					-.08(.12)
Intercept	.57(.05)***	.96(.10)***	.96(.10)***	.60(.07)***	.63(.12)***
Random Part					
Between-level $\sqrt{\psi}$	.117	.148	.134	.134	.136
Within-level $\sqrt{\theta}$	.800	.779	.779	.796	.795
Log-likelihood	-490.3	-478.4	-479.6	-486.7	-449.8
$\mathbf{R^2}$	N/A	.038	.043	.002	.005

Coefficient (Standard Error) * p<0.05; ** p<0.01; *** p<0.001

	Model 5	***Model 6***	***Model 7***	***Model 8.1***	***Model 8.2***
Fixed Part					
Boil: E. Kettles	-.58(.13)***		-.57(.13)***	-.61(.13)***	-.61(.13)***
Boil: Pots	-.36(.14)**		-.37(.14)**	-.45(.14)**	-.45(.14)**
Drink bottled W	-.42(.12)**		-.43(.12)***	-.44(.12)***	-.44(.12)***
Improved W source		-.08(.09)	-.07(.09)	-.04(.09)	-.04(.09)
Safe W storage	-.09(.12)	-.05(.12)	-.05(.12)	-.08(.12)	-.08(.12)
HH head is literate				-.21(.09)*	-.21(.09)*
HH head's age (10yr)				.03(.03)	.03(.03)
HH population				-.00(.02)	
No. TVs in HH				-.38(.20)	-.36(.19)
Intercept	1.01(.15)***	.64(.13)***	1.01(.16)***	1.15(.27)***	1.14(.26)***
Random Part					
Between-level $\sqrt{\psi}$	.153	.157	.172	.162	.162
Within-level $\sqrt{\theta}$	.774	.791	.771	.758	.757
Log-likelihood	-439.9	-447.5	-437.8	-432.4	-429.4
$\mathbf{R^2}$	.046	.005	.045	.083	.083

Coefficient (Standard Error) * p<0.05; ** p<0.01; *** p<0.001

a. Coefficient for a 10 year increase is shown instead of a one year increase

	Model 9.1	*Model 9.2*	*Model 10*	*Model 11*	*Model 12*
Fixed Part					
Boil: E. Kettles	-.62(.13)***	-.62(.13)***	-.6(.13)***	-.6(.13)***	
Boil: Pots	-.44(.14)**	-.46(.14)**	-.44(.14)**	-.43(.14)**	
Drink bottled W	-.45(.13)***	-.46(.13)***	-.45(.13)***	-.45(.13)***	
Improved W source	-.05(.1)	-.05(.1)	-.04(.1)	-.04(.1)	-.05(.1)
Safe W storage	-.08(.12)	-.07(.12)	-.05(.12)	-.05(.13)	-.05(.12)
HH head is literate	-.20(.1)*	-.19(.1)*	-.17(.1)	-.17(.1)	-.16(.1)
HH head's age (10yr)	.04(.03)	.03(.03)	.04(.03)	.04(.04)	.00(.00)
HH population				-.00(.02)	
No. TVs in HH	-.36(.19)	-.35(.19)	-.34(.19)	-.36(.21)	-.27(.2)
Min to health clinic (10)[b]	-.03(.05)			-.01(.00)	
Mean bottled W price	.58(.7)	.56(.7)	.72(.72)	.72(.73)	.27(.72)
Improved latrine	-.03(.11)			-.01(.12)	
Wash post defecation			.07(.09)	.08(.1)	.07(.1)
Soap likely used			-.06(.09)	-.04(.09)	-.1(.09)
Wash before meals			-.2(.13)	-.21(13)	-25(.12)
Intercept	.91(.39)*	.91(.39)*	.92(.4)*	.94(.43)*	.72(.41)
Random Part					
Between-level $\sqrt{\psi}$	.167	.166	.167	.169	.171
Within-level $\sqrt{\theta}$	.760	.757	.758	.762	.778
Log-likelihood	-426.5	-428.5	-428.1	-429.1	-438.8
$\mathbf{R^2}$	.081	.081	.081	.067	.027

Coefficient (Standard Error) * p<0.05; ** p<0.01; *** p<0.001

a. Coefficient for a 10 year increase is shown, instead of a one year increase

b. Coefficient for a 10 minute increase in distance is shown, instead of a one minute increase

6.2 Summary of HWT coefficients from sensitivity analysis

	OLS	*MLE*	*MLE with sample weights at level:*			*Soap present*	*Very safe storage*	*Less strict PD wash*
			1	*2*	*1 & 2*			
Boil: E. Kettles	-.61(.13) ***	-.60(.13) ***	-.59(.14) ***	-.59(.14) ***	-.59(.14) ***	-.59(.13) ***	-.61(.13) ***	-.59(.13) ***
Boil: Pots	-.46(.14) **	-.44(.14) **	-.44(.15) **	-.44(.15) **	-.44(.15) ***	-.44(.14) **	-.46(.14) **	-.44(.14) **
Drink bottled W	-.45(.12) ***	-.45(.12) ***	-.44(.16) **	-.44(.16) **	-.44(.17) *	-.44(.13) ***	-.44(.13) **	-.44(.13) ***

Coefficient (Standard Error)

* p<0.05; ** p<0.01; *** p<0.001

	Without enumerator id. number (n):					*w/o storage*	*w/o source*	*w/o storage & source*
	1 (34)	*10 (22)*	*16 (27)*	*18 (31)*	*22 (27)*			
Boil: E. Kettles	-.58(.13) ***	-.60(.13) ***	-.51(.13) ***	-.60(.14) ***	-.62(.13) ***	-.59(.12) ***	-.60(.13) ***	-.6(.12) ***
Boil: Pots	-.47(.15) **	-.40(.15) **	-.34(.14) *	-.43(.15) **	-.5 (.14) ***	-.45(.14) **	-.43(.14) **	-.45(.13) **
Drink bottled W	-.47(.13) ***	-.46(.13) ***	-.42(.13) **	-.42(.13) **	-.49(.13) ***	-.5(.12) ***	-.44(.12) ***	-.48(.12) ***

Coefficient (Standard Error)

* p<0.05; ** p<0.01; *** p<0.001

	Without hand washing:			*MLM w/3 levels*	*Negative controls & other, DV is:*			
	BM	*PD*	*BM & PD*		*Respondent age*	*Survey duration*	*Enumerator id.*	*HH id. code*
Boil: E. Kettles	-.61(.13) ***	-.60(.13) ***	-.61(.13) ***	-.59(.13) ***	-2.45 (2.10)	-.6 (1.14)	.4 (.55)	.53 (1.41)
Boil: Pots	-.44(.14) **	-.44(.14) **	-.44(.14) **	-.45(.14) **	-.04 (2.28)	-.67 (1.23)	-.54 (.61)	1.16 (1.58)
Drink bottled W	-.45(.13) ***	-.44(.13) ***	-.45(.13) ***	-.45(.13) ***	1.51 (2.04)	.19 (1.1)	.59 (.56)	1.1 (1.45)

Coefficient (Standard Error)

* p<0.05; ** p<0.01; *** p<0.001

	38 outliers removed		38 outliers included	
	Null Model	***Model 10***	***Null Model***	***Model 10***
Fixed Part				
Boil: E. Kettles		-.6(.13)***		-.68(.12)***
Boil: Pots		-.44(.14)**		-.49(.13)***
Drink bottled W		-.45(.13)***		-.56(.12)***
Improved W source		-.04(.1)		-.08(.09)
Safe W storage		-.05(.12)		-.06(.12)
HH head is literate		-.17(.1)		-.11(.09)
HH head's age (10yr)		.04(.03)		.02(.03)
HH population		-.34(.19)		-.32(.18)
No. TVs in HH		.72(.72)		.62(.65)
Min to health clinic (10)[b]		.07(.09)		.04(.09)
Mean bottled W price		-.06(.09)		-.07(.08)
Improved latrine		-.2(.13)		-.21(12)
Intercept	.57(.05)***	.92(.4)*	.55(.04)***	1.13(.37)**
Random Part				
Between-level $\sqrt{\psi}$	.117	.167	.091	.141
Within-level $\sqrt{\theta}$	.800	.758	.800	.756
Log-likelihood	-490.3	-428.1	-535.2	-468.2
R^2	N/A	.081	N/A	.089[b]

Coefficient (Standard Error) * p<0.05; ** p<0.01; *** p<0.001

a. Coefficient for a 10 year increase is shown, instead of a one year increase

b. R^2 calculated based on total variance from the Null Model with 38 outliers removed

7. References

CHAO, K.-K., CHAO, C.-C. & CHAO, W.-L. 2003. Suitability of the traditional microbial indicators and their enumerating methods in the assessment of fecal pollution of subtropical freshwater environments. *Journal of microbiology, immunology, and infection [Chinese]*, 36, 288-293.

RABE-HESKETH, S. & SKRONDAL, A. 2012. *Multilevel and longitudinal modeling using Stata: Volume 1: Continuous responses,* College Station, TX, Stata Press.

WHO 2004. Guidelines for drinking-water quality (third edition), Volume 1: Recommendations. Geneva: World Health Organization.

Appendix IV

Supporting Material for Chapter IV & V

1. Introduction

This appendix presents statistical summaries, plots, analyses, and model outputs used to conduct the analyses presented in chapters four and five. “Courier” font is used throughout this appendix because it is a fixed-width font which allows Stata outputs to remain aligned/legible.

Stats outputs are provided often with some information (e.g., summation rows) in the original Stata outputs truncated in order to save space.

Summary statistics are provided for continuous variables and tabulations provided for binary and categorical variables. Cross-tabs were conducted for all new categorical variables to confirm that the coding worked as expected (they are not presented here in an effort to limit the total number of pages). In cases of more complicated variable creation, the additional steps undertaken are described with Stata outputs, and/or graphs, provided as well. In some cases, the variable code names were changed as the analyses progressed and older versions may also be described/listed here.

Throughout this text, household is often abbreviated as “HH”. Variables not described here but used may be found in Appendix III. Unless otherwise noted, all test statistics and associated p-values presented below are at the 95% Confidence Level and are two-tailed.

2. Response variables (dependent variables)

2.1 HWT Method data: Boil/Untreated (BoilUn_D)

A new variable was created (based on BlBtUn, see Appendix III) called BoilUn_D such that boiling by any means = 1 and drinking untreated water = 0 and all other cases (bottled) are marked “.b” (treated as MD) and MD marked “.m”.

BoilUn_D dummy created based on BlBtUn:

```
Cat: Boil, |
  Bottled, |
        or |           Boil=1, Untreated=0
 Untreated | Untreated       Boil         .b         .m |     Total
-----------+--------------------------------------------+----------
      Boil |         0        215          0          0 |       215
   Bottled |         0          0        157          0 |       157
 Untreated |        75          0          0          0 |        75
        .m |         0          0          0          3 |         3
-----------+--------------------------------------------+----------
     Total |        75        215        157          3 |       450
```

2.2 HWT Method data: Kettle/Pot (KettlePot_D)

A new variable was created (based on Bl2BtUn, see Appendix III) called KettlePot_D such that boiling with an electric kettle = 1 and boiling with a pot =0. Bottled water cases are marked ".b", untreated cases marked ".u.", and MD marked ".m".

Cat: Boil-E. Kettle, Boil-Pot, Bottled, Untreated	KettlePot_D					
	Boil: Pot	Boil: E.	.b	.m	.u	Total
Boil: Elec. Kettle	0	122	0	0	0	122
Boil: Pot	93	0	0	0	0	93
Bottled Water	0	0	157	0	0	157
Untreated Water	0	0	0	0	75	75
.m	0	0	0	3	0	3
Total	93	122	157	3	75	450

2.3 HWT Method data: Bottled/Boil (BtlBoil_D)

A new variable was created (based on BlBtUn, see Appendix III) called BtlBoil_D such that bottled water = 1 and boiling (by any means) =0 and untreated cases are marked ".u" (treated as MD).

BtlBoil_D dummy created based on BlBtUn:

Cat: Boil, Bottled, or Untreated	Bottled=1, Boil=0				
	Boil	Bottle	.m	.u	Total
Boil	215	0	0	0	215
Bottled	0	157	0	0	157
Untreated	0	0	0	75	75
.m	0	0	3	0	3
Total	215	157	3	75	450

3. Covariates (independent variables)

3.1 Demographic covariates

3.1.1 Head of the HH's age: head_hh_age

Head of Households's Age

	Percentiles	Smallest		
1%	26	24		
5%	32	25		
10%	35	25	Obs	449
25%	43	25	Sum of Wgt.	449
50%	52		Mean	52.39644
		Largest	Std. Dev.	12.49245
75%	61	79		
90%	70	80	Variance	156.0612
95%	74	80	Skewness	.0516859
99%	78	80	Kurtosis	2.288308

3.1.2 Head of the HH's gender dummy: HHgender_D

Dummy: Male=1, other=0	County Code: County A	County B	Total
Female or F&M	67	8	75
	27.92	3.81	16.67
Male	171	202	373
	71.25	96.19	82.89

3.1.3 HH size – total number of people (in and out) HH: HHp_total_in_o

Total HH Population (living in & out HH)

	Percentiles	Smallest		
1%	1	1		
5%	2	1		
10%	3	1	Obs	450
25%	4	1	Sum of Wgt.	450
50%	5		Mean	5.353333

		Largest	Std. Dev.	2.297874
75%	6	12		
90%	8	14	Variance	5.280223
95%	9	16	Skewness	1.582583
99%	12	22	Kurtosis	9.784315

3.2 Behavioral & psychological covariates

3.2.1 Perception that most/all relatives in area boil water: RelativesBoil_D

Number of relatives in village/area who boil W (Q86)	Number of HHs in village/area who boil W (Q87): Don't kno	None	Some	About hal	Most	All	Total
Don't know	177	0	10	3	9	0	199
None	2	2	1	0	0	0	5
Some	9	1	31	7	3	0	51
About half	5	0	1	59	3	0	68
Most	7	0	2	6	108	0	123
All	0	0	0	0	0	2	2
Total	200	3	45	75	123	2	448

As such, this dummy is based on Q86 such that if the perception is that "most" or "all" of their relatives boil then this dummy =1, and otherwise =0.

Dummy: Most or all boil=1	County Code: County A	County B	Total
None, some or about h	55	69	124
	22.92	32.86	27.56
Most or all boil	106	19	125
	44.17	9.05	27.78

3.2.2 Perception that most/all HHs in area boil water: NeighborsBoil_D

Following the logic above, this dummy is based on Q87 such that if the perception is that "most" or "all" of their neighbors boil then this dummy =1, and otherwise =0.

Dummy: Most or all boil=1	County Code: County A	County B	Total
None, some or about h	54	70	124
	22.50	33.33	27.56
Most or all boil	104	21	125
	43.33	10.00	27.78

3.2.3 Perception of water quality: PercWQ_D

Q38 asks about the respondent's perception of their water quality and is used to create a simple binary dummy PercWQ_D such that "good" and "very good" = 1:

Dummy: Good, very good=1	County Code: County A	County B	Total
Poor or satisfactory	172	66	238
	71.67	31.43	52.89
Good or very good	55	136	191
	22.92	64.76	42.44

3.2.4 Belief that drinking untreated water is not harmful: PercNoTreatOK_D

Q93 asks respondents what they believe will happen if someone drinks untreated water. The various responses are broken into two categories for a dummy variable: nothing will happen=1, something negative will happen=0.

Dummy: Drinking untreated W not harmful=1	County Code: County A	County B	Total
Will get sick	164	46	210
	68.33	21.90	46.67
Nothing will happen	68	156	224
	28.33	74.29	49.78

3.2.5 Reason don't drink bottled water ("other" responses re-coded): 4-category dummy

Q104 asks HHs that don't buy/drink bottled water why they don't. The responses are listed below based on the HH's primary HWT method.

Why HH does not drink bottled W (Q104)	Cat: Boil, Bottled, or Untreated Boil	Bottled	Untreated	.m	Total
Too expensive	78	0	21	0	99
Not easy to get	34	0	3	0	37
Not safe	29	0	7	0	36
Don't know	11	0	7	2	20
Other	54	0	32	1	87
.m	9	0	4	0	13
.s	0	157	1	0	158
Total	215	157	75	3	450

Given that 87 HHs (31% of the data for Q104) responded "other", the notes enumerators made for Q104 (which were entered into the original Excel data files) were examined for each HH in order to re-code as many of these response as possible. Of these 87 other responses some responses were re-assigned existing codes (e.g., "not convenient to buy it" assigned response 2, "Not easy to get it") and for the majority of the remaining responses these new responses/codes were used:

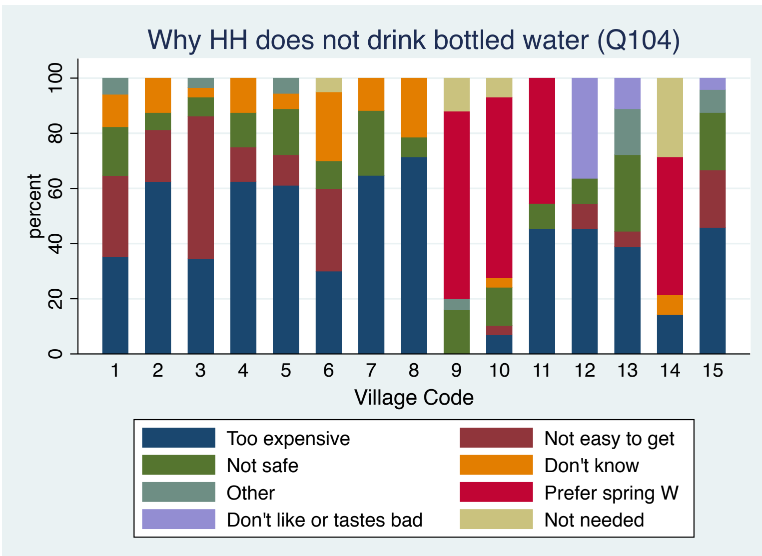
6. Prefer spring W
7. Boiled W is safe/preferred – this was then re-coded as 3 "not safe"
8. Don't like or tastes bad [Don't like it –or- Does not taste good]
9. Not needed [No need for bottled water –or- Not necessary to buy]

In this way, 78 of the 87 "other" responses were re-assigned or re-coded, as follows:

Why HH does not drink bottled W (Q104)	Cat: Boil, Bottled, or Untreated Boil	Bottled	Untreated	.m	Total
Too expensive	82	0	24	0	106
Not easy to get	36	0	5	0	41
Not safe	31	0	7	0	38
Don't know	11	0	7	2	20
Other	6	0	3	0	9
Prefer spring W	31	0	16	1	48
Don't like or tastes	4	0	3	0	7
Not needed	5	0	5	0	10
.m	9	0	4	0	13
.s	0	157	1	0	158
Total	215	157	75	3	450

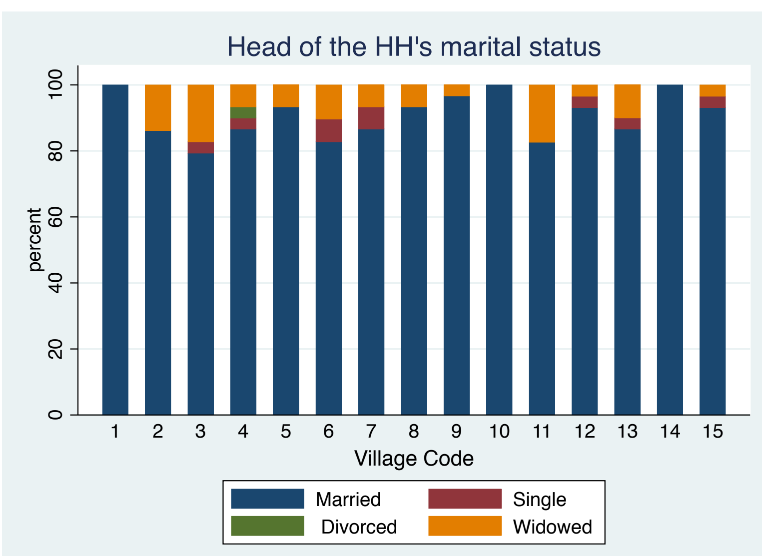
These dummy variables were then created:

	Q104e	Q104i	Q104u	Q104s
Too expensive	1	0	0	0
Inconvenient to get	0	1	0	0
Unsafe	0	0	1	0
Prefer spring W	0	0	0	1



3.3 Demographic/Socioeconomic and related covariates

3.3.1 Head of HH marital status dummy (married=1): Marital_D



Dummy: Married=1, other=0	County A	County B	Total
Single, divorced or w	27	13	40
	11.25	6.19	8.89
Married	210	185	395
	87.50	88.10	87.78
.m	3	12	15
	1.25	5.71	3.33
Total	240	210	450
	100.00	100.00	100.00

3.3.2 Number of TVs per adults living in HH: TVbyHH

TV ownership provides a good proxy for HH wealth, but one would expect that HHs with larger populations might have more TVs so a new variable was created to adjust TV ownership (Q71) by HH size (q71/HHp_a_in"):

Summary for variables: TVbyHH
by categories of: aa1 (County Code)

aa1	min	p50	max	mean	sd	N
County A	0	.5	2	.5317275	.3699133	235
County B	0	.5	4	.6652129	.4630742	208
Total	0	.5	4	.5944023	.4210906	443

3.3.3 Average cost of bottled water per village: RMBvillageBottle_r

This variable is a calculation of the average cost in RMB per liter for each village based on the costs for those HHs which use bottled water, assuming there were at least two HHs per village with data on bottled water costs.

Village	mean
1	.4673721
2	.5736961
3	.
4	.4477004
5	.4126984
6	.4115226
7	.5026455

8	.4861111
9	.
10	.
11	.3894768
12	.3797074
13	.3395062
14	.218254
15	.2645503
Total	.4077701

Check against q76_RMB_L means by village:

aa3	min	p50	max	mean	sd	N
1	.3174603	.4761905	.6349207	.4673721	.0776087	12
2	.4232804	.4232804	2	.5736961	.4340545	14
3	2	2	2	2	.	1
4	.4232804	.4232804	.4761905	.4477004	.0274537	13
5	.3703704	.4232804	.4761905	.4126984	.041736	10
6	.3703704	.4232804	.4232804	.4115226	.0233311	9
7	.4232804	.4761905	.7936508	.5026455	.0996263	12
8	.4761905	.4761905	.5291005	.4861111	.0213287	16
9	.2116402	.2116402	.2116402	.2116402	.	1
10	.	.	.	.	.	0
11	.1851852	.3439153	.6878307	.3894768	.1620174	18
12	.2116402	.4232804	.5291005	.3797074	.1045481	17
13	.2645503	.2645503	.5291005	.3395062	.1045093	12
14	.2116402	.2116402	.2645503	.218254	.0180722	16
15	.2116402	.2116402	.4761905	.2645503	.1183105	5
Total	.1851852	.4232804	2	.4209402	.2187542	156

In order to avoid creating too much MD, for villages three, nine and ten, the county means were used, such that the value for Village Three = .471678 RMB and the values for Villages Nine and Ten = .3182989 RMB. Thus the resulting variable name “RMBvillageBottle_r” has an “_r” added to indicate that it was revised in this fashion.

These village averages were multiplied by 19 in order to create a new variable, “RMBvillageBottle_r19”, that represented the average cost for a large 19L bottle of water per village.

3.3.4 HH’s ability to afford healthcare for serious illness/injury: AffordProfCare_D

Q14 asks if the HH can afford professional treatment for serious illness or injury. If the response was “Yes, because government or employer helps pay for treatment” or “Yes, household can afford it” AffordProfCare_D =1, and 0 if otherwise.

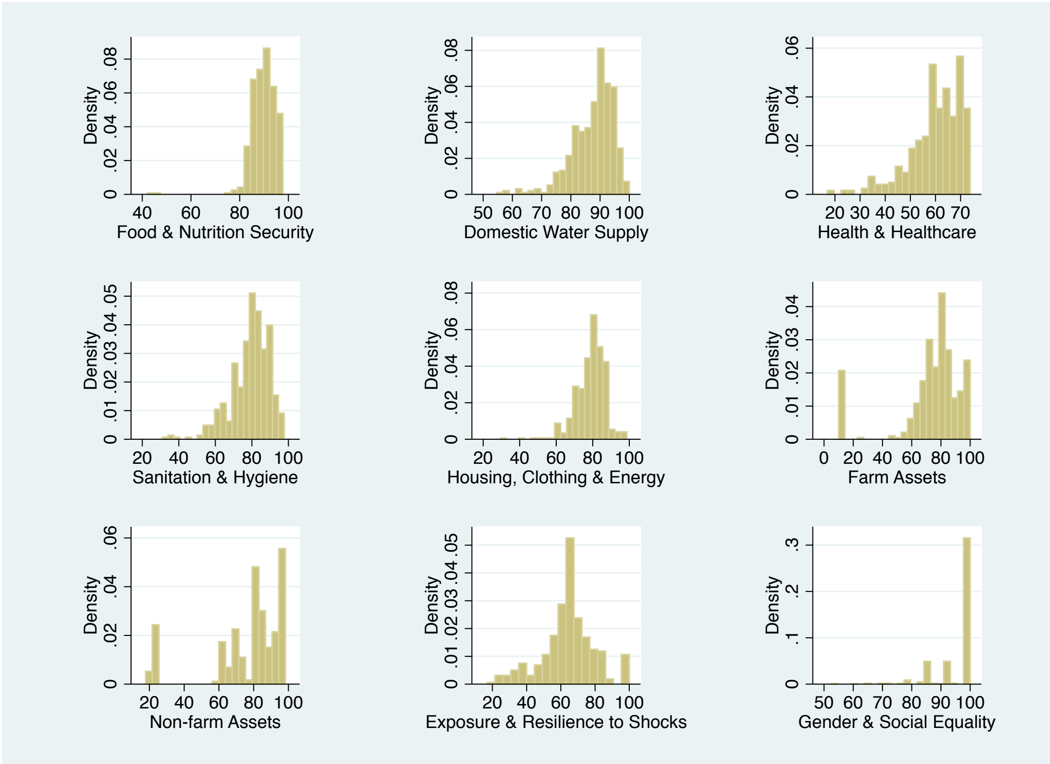
HH can afford prof. healthcare=1, other=0	County Code: County A	County B	Total
No or only w difficul	172	27	199
	71.67	12.86	44.22
Yes, can afford or go	68	183	251
	28.33	87.14	55.78
Total	240	210	450
	100.00	100.00	100.00

3.4 Covariates derived from MPAT: Steps taken for exploratory analysis

3.4.1 Descriptive statistics for the MPAT components

TOTAL SAMPLE

Variable	N	Mean	SD	Median	Min	
MPAT_C1	450	89.67	5.08	90.00	42.10	Food & Nutrition Security
MPAT_C2	450	87.58	7.05	89.85	54.60	Domestic Water Supply
MPAT_C3	450	60.12	10.31	61.50	17.00	Health & Healthcare
MPAT_C4	450	79.21	10.48	80.70	31.00	Sanitation & Hygiene
MPAT_C5	450	78.93	8.21	80.70	29.50	Housing, Clothing & Energy
MPAT6_3	195	90.24	10.03	90.00	45.00	Education Access
MPAT_C7	450	73.69	22.80	79.10	10.00	Farm Assets
MPAT_C8	450	76.03	21.45	80.80	17.80	Non-farm Assets
MPAT_C9	346	64.27	15.48	64.60	16.90	Exposure & Resilience to Shocks
MPAT_C10	450	95.95	7.41	100.00	52.50	Gender & Social Equality

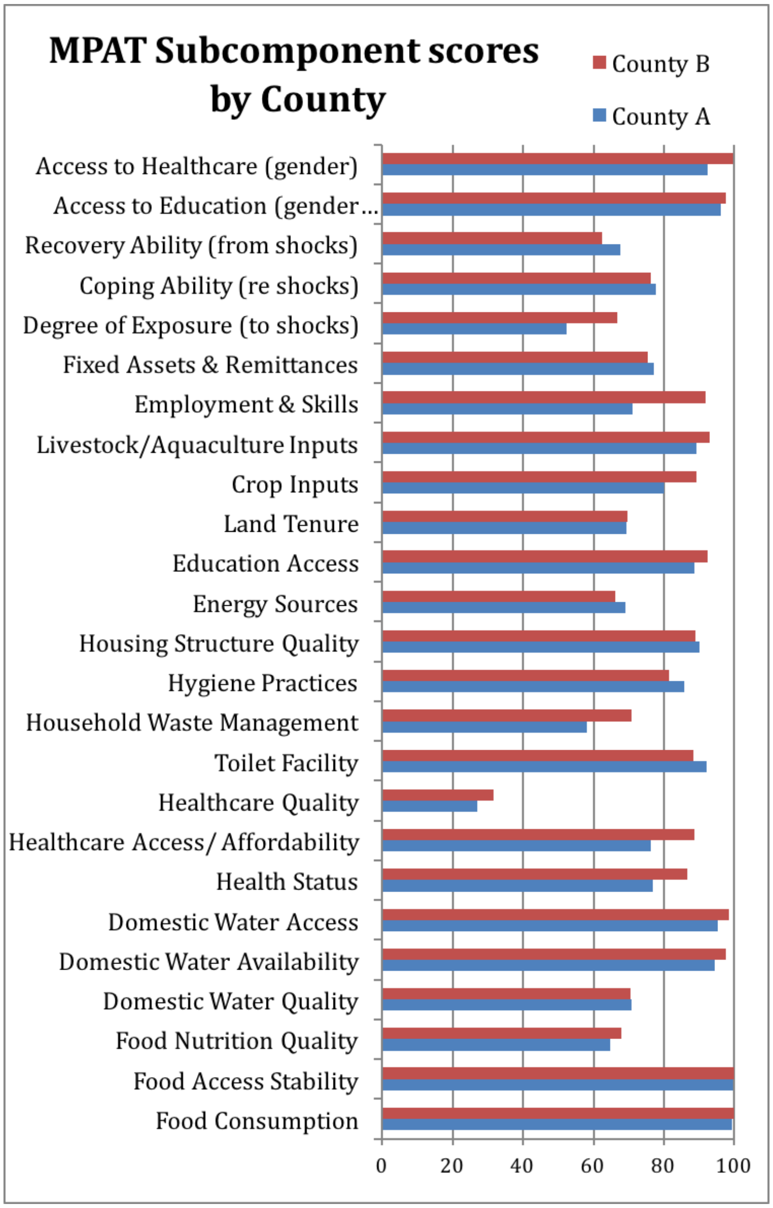


3.4.3 Descriptive statistics for the MPAT subcomponents

TOTAL SAMPLE

Variable	N	Mean	SD	Median	Min	
MPAT1_1	448	99.64	4.22	100.00	20.00	Food Consumption
MPAT1_2	450	99.83	2.67	100.00	50.50	Food Access Stability
MPAT1_3	450	66.23	11.59	66.00	38.00	Food Nutrition Quality
MPAT2_1	450	70.54	11.89	71.30	29.30	Domestic Water Quality
MPAT2_2	450	95.87	9.78	100.00	35.50	Domestic Water Availability
MPAT2_3	450	96.78	6.94	100.00	64.00	Domestic Water Access
MPAT3_1	450	81.44	18.52	86.00	10.00	Health Status
MPAT3_2	450	81.94	11.89	88.00	42.00	Healthcare Access/Affordability
MPAT3_3	445	29.03	8.51	35.30	7.10	Healthcare Quality
MPAT4_1	450	90.20	11.89	94.00	10.00	Toilet Facility
MPAT4_2	443	63.91	18.96	65.40	13.80	Household Waste Management
MPAT4_3	450	83.76	12.70	86.50	32.30	Hygiene Practices
MPAT5_1	450	89.62	10.71	94.00	23.00	Housing Structure Quality
MPAT5_3	450	67.66	10.77	73.00	28.60	Energy Sources
MPAT6_3	195	90.24	10.03	90.00	45.00	Education Access
MPAT7_1	450	69.51	24.11	75.00	10.00	Land Tenure
MPAT7_3	374	84.16	12.97	83.90	43.10	Crop Inputs
MPAT7_4	112	89.96	15.02	100.00	14.00	Livestock/Aquaculture Inputs
MPAT8_1	443	80.88	30.32	100.00	10.00	Employment & Skills
MPAT8_3	450	76.20	13.29	80.00	40.00	Fixed Assets & Remittances

MPAT9_1	346	58.40	26.97	50.00	10.00	Degree of Exposure (to shocks)
MPAT9_2	271	77.11	7.69	80.00	15.00	Coping Ability (re shocks)
MPAT9_3	326	65.61	13.60	70.00	22.00	Recovery Ability (from shocks)
MPAT10_1	273	96.79	9.59	100.00	50.00	Access to Education (gender eq)
MPAT10_2	450	95.71	8.03	100.00	52.50	Access to Healthcare (gender)



3.4.4 Domestic Water Supply Component and associations with TTC

We can compare the Domestic Water Quality subcomponent scores for water quality with the mean levels of TTC detected to see how well this proxy for water quality compares with the actual water quality data.

```
Two-sample t test with unequal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
No TTC ( |     272     71.7761    .6818736    11.24575    70.43366    73.11855
TTC dete |     172     68.7314    .9612708    12.60695    66.83391    70.62888
---------+--------------------------------------------------------------------
combined |     444    70.59662      .56337    11.87094    69.48941    71.70383
---------+--------------------------------------------------------------------
    diff |            3.044708    1.178556                .7263592    5.363056
------------------------------------------------------------------------------
    diff = mean(No TTC () - mean(TTC dete)                        t =   2.5834
Ho: diff = 0                     Satterthwaite's degrees of freedom =  333.155

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9949         Pr(|T| > |t|) = 0.0102          Pr(T > t) = 0.0051
```

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

  TTC_cont_D |      obs    rank sum    expected
-------------+---------------------------------
No TTC (BDL) |      272       63306       60520
TTC detected |      172       35484       38270
-------------+---------------------------------
    combined |      444       98790       98790

unadjusted variance  1734906.67
adjustment for ties    -3792.94
                     ----------
adjusted variance    1731113.73

Ho: MPAT2_1(TTC_co~D==No TTC (BDL)) = MPAT2_1(TTC_co~D==TTC detected)
             z =   2.117
    Prob > |z| =   0.0342
```

```
Summary for variables: TTCmL10_or
     by categories of: q38 (Perception of drinking water quality (Q38))

         q38 |       min       p50       max      mean        sd         N
-------------+------------------------------------------------------------
  Don't know |         0         0  2.230449  .5558914  .8542602        18
        Poor |         0         0  2.380211  .6367177  .8774986        11
Satisfactory |         0         0  2.732394  .6252319  .8024323       203
        Good |         0         0  2.544068  .4965647  .8095445       145
   Very good |         0         0  2.113943  .4700676   .807768        28
-------------+------------------------------------------------------------
       Total |         0         0  2.732394  .5656686  .8082012       405
--------------------------------------------------------------------------
```

```
Summary for variables: TTC_or
     by categories of: q38 (Perception of drinking water quality (Q38))

         q38 |       min       p50       max      mean        sd         N
-------------+------------------------------------------------------------
  Don't know |         0         0       170  24.55556  50.19049        18
        Poor |         0         0       240  30.63636  71.37124        11
Satisfactory |         0         0       540  29.50739  77.85677       203
        Good |         0         0       350  28.34483  68.72301       145
   Very good |         0         0       130     21.25  45.88038        28
-------------+------------------------------------------------------------
       Total |         0         0       540  28.33086   71.3579       405
--------------------------------------------------------------------------
```

3.4.5 Step 1: Stepwise logistic regression with MPAT components

Due to missing data from censored questions and the absence of the MPAT Village Survey results (see Chapter II), there was too much missing data to calculate the following subcomponents: 5.2, 6.1, 6.2, 7.2, 8.2, 10.3. Consequently, for this initial analysis with the MPAT component results, subcomponent 6.3 (MPAT6_3) is used in place of component six (MPAT_C6).

First, stepwise logistic regression was used with the MPAT component values and a probability threshold of 0.2 for addition to the model. Backward stepwise logistic regression was then used with a probability threshold of 0.2 for removal from the model. MPAT components that had no association with the DVs in both models were not included in the next step of modeling.

. stepwise, pe(.2): logistic BoilUn_D MPAT_C1 MPAT_C2 MPAT_C3 MPAT_C4 MPAT_C5 MPAT6_3 MPAT_C7 MPAT_C8 MPAT_C9 MPAT_C10

```
Logistic regression                               Number of obs   =         92
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT_C5 |   1.148362   .0452801     3.51   0.000     1.062957    1.240629
     MPAT_C3 |   .9553423   .0262437    -1.66   0.096     .9052658    1.008189
     MPAT6_3 |    .962418   .0268757    -1.37   0.170     .9111582    1.016562
       _cons |   .0293298   .1079728    -0.96   0.338     .0000216     39.8902
------------------------------------------------------------------------------
```

. stepwise, pr(.2): logistic BoilUn_D MPAT_C1 MPAT_C2 MPAT_C3 MPAT_C4 MPAT_C5 MPAT6_3 MPAT_C7 MPAT_C8 MPAT_C9 MPAT_C10

```
Logistic regression                               Number of obs   =         92
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT6_3 |   .9630988   .0278208    -1.30   0.193     .9100858      1.0192
     MPAT_C2 |   1.067727   .0392753     1.78   0.075     .9934585    1.147548
    MPAT_C10 |   .9154739   .0422452    -1.91   0.056     .8363088    1.002133
     MPAT_C8 |   .9797472   .0156366    -1.28   0.200     .9495744    1.010879
```

```
    MPAT_C5 |   1.109399    .044678     2.58   0.010     1.025198    1.200515
      _cons |   2.130153   11.76903     0.14   0.891     .0000422    107465.9
------------------------------------------------------------------------------
```

```
. stepwise, pe(.2): logistic BtlUn_D MPAT_C1 MPAT_C2 MPAT_C3 MPAT_C4 MPAT_C5 MPAT6_3 MPAT_C7
MPAT_C8 MPAT_C9 MPAT_C10
Logistic regression                               Number of obs   =         79
------------------------------------------------------------------------------
    BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_C5 |   1.157151   .0507726     3.33   0.001     1.061797    1.261068
    MPAT_C2 |   1.081686    .048458     1.75   0.080     .9907604    1.180956
      _cons |   3.01e-08   1.45e-07    -3.59   0.000     2.35e-12    .0003858
------------------------------------------------------------------------------
```

```
. stepwise, pr(.2): logistic BtlUn_D MPAT_C1 MPAT_C2 MPAT_C3 MPAT_C4 MPAT_C5 MPAT6_3 MPAT_C7
MPAT_C8 MPAT_C9 MPAT_C10
Logistic regression                               Number of obs   =         79
------------------------------------------------------------------------------
    BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_C5 |   1.157151   .0507726     3.33   0.001     1.061797    1.261068
    MPAT_C2 |   1.081686    .048458     1.75   0.080     .9907604    1.180956
      _cons |   3.01e-08   1.45e-07    -3.59   0.000     2.35e-12    .0003858
------------------------------------------------------------------------------
```

3.4.6 Step 1: Summary of potentially relevant MPAT components

MPAT Component	Boil/Untreated	Bottled/Untreated
2	x	x
3	x	
5	x	x
6.3	x	
8	x	
10	x	

3.4.7 Step 2: Stepwise logistic regression with MPAT subcomponents

Second, stepwise logistic regression was used with all the MPAT subcomponent results belonging to the MPAT components identified in the previous stage, using a probability threshold of 0.15, with subcomponents added to the model and then removed from the model. This step was used to identify which MPAT subcomponents might contain survey questions significantly associated with the DVs.

```
. stepwise, pe(.15): logistic BoilUn_D MPAT2_1 MPAT2_2 MPAT2_3 MPAT3_1 MPAT3_2 MPAT3_3 MPAT5_1
MPAT5_3 MPAT6_3 MPAT8_1 MPAT8_3 MPAT10_1 MPAT10_2
Logistic regression                               Number of obs   =        115
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT2_1 |   1.090498   .0256989     3.68   0.000     1.041275    1.142049
     MPAT3_2 |   .9334169   .0249922    -2.57   0.010     .8856963    .9837087
    MPAT10_2 |   .8835567   .0434241    -2.52   0.012     .8024177    .9729003
     MPAT5_1 |   1.052816   .0300691     1.80   0.072     .9955009    1.113431
       _cons |   3256.586   19172.82     1.37   0.169     .0317248    3.34e+08
------------------------------------------------------------------------------

. stepwise, pr(.15): logistic BoilUn_D MPAT2_1 MPAT2_2 MPAT2_3 MPAT3_1 MPAT3_2 MPAT3_3 MPAT5_1
MPAT5_3 MPAT6_3 MPAT8_1 MPAT8_3 MPAT10_1 MPAT10_2
Logistic regression                               Number of obs   =        115
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT2_1 |   1.090498   .0256989     3.68   0.000     1.041275    1.142049
     MPAT3_2 |   .9334169   .0249922    -2.57   0.010     .8856963    .9837087
    MPAT10_2 |   .8835567   .0434241    -2.52   0.012     .8024177    .9729003
     MPAT5_1 |   1.052816   .0300691     1.80   0.072     .9955009    1.113431
       _cons |   3256.586   19172.82     1.37   0.169     .0317248    3.34e+08
------------------------------------------------------------------------------

. stepwise, pe(.15): logistic BtlUn_D MPAT2_1 MPAT2_2 MPAT2_3 MPAT3_1 MPAT3_2 MPAT3_3 MPAT5_1
MPAT5_3 MPAT6_3 MPAT8_1 MPAT8_3 MPAT10_1 MPAT10_2
Logistic regression                               Number of obs   =        104
------------------------------------------------------------------------------
     BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT5_3 |   1.084714   .0282068     3.13   0.002     1.030815    1.141432
     MPAT2_1 |    1.04853   .0218259     2.28   0.023     1.006613    1.092192
     MPAT5_1 |   1.056102   .0269166     2.14   0.032     1.004642    1.110197
       _cons |   3.02e-06   9.82e-06    -3.90   0.000     5.10e-09    .0017839
------------------------------------------------------------------------------

. stepwise, pr(.15): logistic BtlUn_D MPAT2_1 MPAT2_2 MPAT2_3 MPAT3_1 MPAT3_2 MPAT3_3 MPAT5_1
MPAT5_3 MPAT6_3 MPAT8_1 MPAT8_3 MPAT10_1 MPAT10_2
Logistic regression                               Number of obs   =        104
------------------------------------------------------------------------------
     BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     MPAT2_1 |    1.04853   .0218259     2.28   0.023     1.006613    1.092192
     MPAT5_3 |   1.084714   .0282068     3.13   0.002     1.030815    1.141432
     MPAT5_1 |   1.056102   .0269166     2.14   0.032     1.004642    1.110197
       _cons |   3.02e-06   9.82e-06    -3.90   0.000     5.10e-09    .0017839
------------------------------------------------------------------------------
```

3.4.8 Step 2: Summary of potentially relevant MPAT subcomponents

MPAT Subcomponent	Boil/Untreated	Bottled/Untreated
2.1	x	x
3.2	x	
5.1	x	x
5.3		x
10.2	x	

3.4.9 Step 3: Potentially relevant survey items: Variable preparation

One of the benefits of the way MPAT is calculated is that in addition to have component and subcomponent scores for each HH, the cardinalized values are available for each survey question as well. The cardinal scores can be found in the 2014 MPAT User's Guide and/or on the 2014 MPAT Excel Spreadsheet, at www.ifad.org/mpat. New variables were created using these survey item response values. Cross-tabulations were conducted to confirm the accurate creation of the newly named variables for this step (outputs not shown).

3.4.10 Step 3: Stepwise logistic regression with MPAT survey items

With these variables prepared, the third step of the process was then conducted to identify which specific survey items (survey questions) from the MPAT subcomponents identified in step two would remain in the models. For this third round, a probability threshold of 0.15 was used.

```
. stepwise, pe(.15): logistic BoilUn_D MPAT_Q32 MPAT_Q34 MPAT_Q38 MPAT_Q11 MPAT_Q13 MPAT_Q14
MPAT_Q17 MPAT_Q19 MPAT_Q21 MPAT_Q22 MPAT_Q15 MPAT_Q16
note: MPAT_Q15 dropped because of estimability
note: o.MPAT_Q15 dropped because of estimability
note: 1 obs. dropped because of estimability
Logistic regression                              Number of obs   =        168
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_Q34 |   2.715396   .4540974     5.97   0.000     1.956529    3.768601
    MPAT_Q14 |   .6944521   .1406166    -1.80   0.072     .4669669    1.032758
    MPAT_Q21 |   1.533578   .3268909     2.01   0.045     1.009874    2.328865
    MPAT_Q13 |   .4964843   .2406263    -1.44   0.149     .1920268    1.283658
       _cons |   4.652248   20.26959     0.35   0.724       .00091    23784.94
------------------------------------------------------------------------------
```

. stepwise, pr(.15): logistic BoilUn_D MPAT_Q32 MPAT_Q34 MPAT_Q38 MPAT_Q11 MPAT_Q13 MPAT_Q14 MPAT_Q17 MPAT_Q19 MPAT_Q21 MPAT_Q22 MPAT_Q15 MPAT_Q16

```
note: MPAT_Q15 dropped because of estimability
note: o.MPAT_Q15 dropped because of estimability
note: 1 obs. dropped because of estimability
Logistic regression                               Number of obs   =        168
------------------------------------------------------------------------------
    BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_Q13 |   .4964843   .2406263    -1.44   0.149     .1920268    1.283658
    MPAT_Q34 |   2.715396   .4540974     5.97   0.000     1.956529    3.768601
    MPAT_Q21 |   1.533578   .3268909     2.01   0.045     1.009874    2.328865
    MPAT_Q14 |   .6944521   .1406166    -1.80   0.072     .4669669    1.032758
       _cons |   4.652248   20.26959     0.35   0.724       .00091    23784.94
------------------------------------------------------------------------------
```

. stepwise, pe(.15): logistic BtlUn_D MPAT_Q32 MPAT_Q34 MPAT_Q38 MPAT_Q11 MPAT_Q13 MPAT_Q14 MPAT_Q17 MPAT_Q19 MPAT_Q21 MPAT_Q22 MPAT_Q15 MPAT_Q16

```
note: MPAT_Q15 dropped because of collinearity
Logistic regression                               Number of obs   =        122
------------------------------------------------------------------------------
     BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_Q34 |   1.972869   .2671241     5.02   0.000     1.513027    2.572468
    MPAT_Q21 |   1.781522   .3606964     2.85   0.004     1.197988    2.649293
    MPAT_Q32 |    1.54431   .3385675     1.98   0.047     1.004895    2.373275
    MPAT_Q14 |   .7133779   .1215802    -1.98   0.048     .5107993    .9962975
    MPAT_Q11 |   7.259621    5.95714     2.42   0.016     1.453551    36.25748
    MPAT_Q17 |   1.932155   .7500575     1.70   0.090     .9028341    4.135007
       _cons |   5.18e-15   5.46e-14    -3.12   0.002     5.49e-24    4.88e-06
------------------------------------------------------------------------------
```

. stepwise, pr(.15): logistic BtlUn_D MPAT_Q32 MPAT_Q34 MPAT_Q38 MPAT_Q11 MPAT_Q13 MPAT_Q14 MPAT_Q17 MPAT_Q19 MPAT_Q21 MPAT_Q22 MPAT_Q15 MPAT_Q16

```
note: MPAT_Q15 dropped because of collinearity
Logistic regression                               Number of obs   =        122
------------------------------------------------------------------------------
     BtlUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    MPAT_Q32 |    1.54431   .3385675     1.98   0.047     1.004895    2.373275
    MPAT_Q34 |   1.972869   .2671241     5.02   0.000     1.513027    2.572468
    MPAT_Q21 |   1.781522   .3606964     2.85   0.004     1.197988    2.649293
    MPAT_Q11 |   7.259621    5.95714     2.42   0.016     1.453551    36.25748
    MPAT_Q17 |   1.932155   .7500575     1.70   0.090     .9028341    4.135007
    MPAT_Q14 |   .7133779   .1215802    -1.98   0.048     .5107993    .9962975
       _cons |   5.18e-15   5.46e-14    -3.12   0.002     5.49e-24    4.88e-06
------------------------------------------------------------------------------
```

3.4.11 Step 3: Summary of potentially relevant MPAT survey questions

MPAT Survey Question	Boil/Untreated	Bottled/Untreated
11		x
13	x	
14	x	x
17		x
21	x	x
32		x
34	x	x

3.5 Description of MPAT-derived covariate creation and use

For some of these items it seems sensible to stay with the MPAT values, but for others it was more appropriate to break the survey responses into binary dummy variables. Some of these variables were already constructed (see Appendix III), newly constructed variables are presented here.

3.5.1 Time to reach clinic that can provide advanced healthcare (Q13): AdvHealthAccess

Q13 measures the number of minutes needed to arrive (by any method) at the nearest health center that can address serious illness or injury. Rather than using the MPAT values we can keep the variable in its semi-continuous format.

There were two HHs which reported that the health center was too far to reach, both in village five; however, the mean number of minutes for village five (excluding these two HHs) is 34.1 (SD=12.1) with a max of 60 minutes, so for this analysis the values from these two HHs were changed to 60 minutes (hence the new variable AdvHealthAccess).

```
      Minutes to reach health center which can provide
                     advanced healthcare
-------------------------------------------------------------
      Percentiles      Smallest
 1%            2              1
 5%            5              1
10%           10              2       Obs                 446
25%           15              2       Sum of Wgt.         446

50%           30                      Mean           26.08072
                        Largest       Std. Dev.      14.60469
75%           30             60
```

90%	40	80	Variance	213.2968
95%	60	85	Skewness	1.269583
99%	60	120	Kurtosis	7.274242

3.5.2 Can household afford professional healthcare if they wish to (Q14): AffordProfCare_D

HH can afford prof. healthcare=1, other=0	Cat: Boil-E. Kettle, Boil-Pot, Bottled, Untreated Boil: Ele	Boil: Pot	Bottled W	Untreated	.m	Total
No or only w difficul	59	53	62	23	2	199
Yes, can afford or go	63	40	95	52	1	251
Total	122	93	157	75	3	450

3.5.5 Home's ability to withstand severe weather (Q19 [sub for Q17]): HomeDurability_D

Where one to use the data from Q17 to create a binary variable it would be of limited usefulness considering that 97.78% of HHs had walls constructed with relatively high-quality materials, as shown below.

Housing exterior wall material (Q17)	HomeWalls_D 0	1	.	Total
Reinforced concrete	0	50	0	50
Stone & mortar	0	4	0	4
Cement blocks	0	243	0	243
Brick (fired/burned)	0	143	0	143
Brick (mud or earth)	5	0	0	5
Earth or adobe	3	0	0	3
Other	1	0	0	1
.m	0	0	1	1
Total	9	440	1	450

Thus, a related proxy was used instead, based on Q19 which asks respondent's if they believe their home could withstand a severe weather event. A dummy variable was created such that responses "yes" and "yes, with minor damage" = 1, other =0.

Dummy: Home is durable=1	Cat: Boil-E. Kettle, Boil-Pot, Bottled, Untreated Boil: Ele	Boil: Pot	Bottled W	Untreated	.m	Total
Home cannot withstand	8	12	27	8	0	55
Home can withstand ex	109	74	122	64	3	372
.	5	7	8	3	0	23

Total	122	93	157	75	3	450

3.5.6 Quality of fuel used for cooking (Q21): SafeFuel_D

A dummy variable was created such that safe fuels (those with low potential to generate indoor air pollution) =1 and unsafe fuels/other = 0.

Dummy: Safe fuel=1, other=0	Cat: Boil-E. Kettle, Boil-Pot, Bottled, Untreated Boil: Ele	Boil: Pot	Bottled W	Untreated	.m	Total
Unsafe fuel (IAP pote	22	52	28	28	2	132
Safe fuel	97	36	120	47	1	301
.	3	5	9	0	0	17
Total	122	93	157	75	3	450

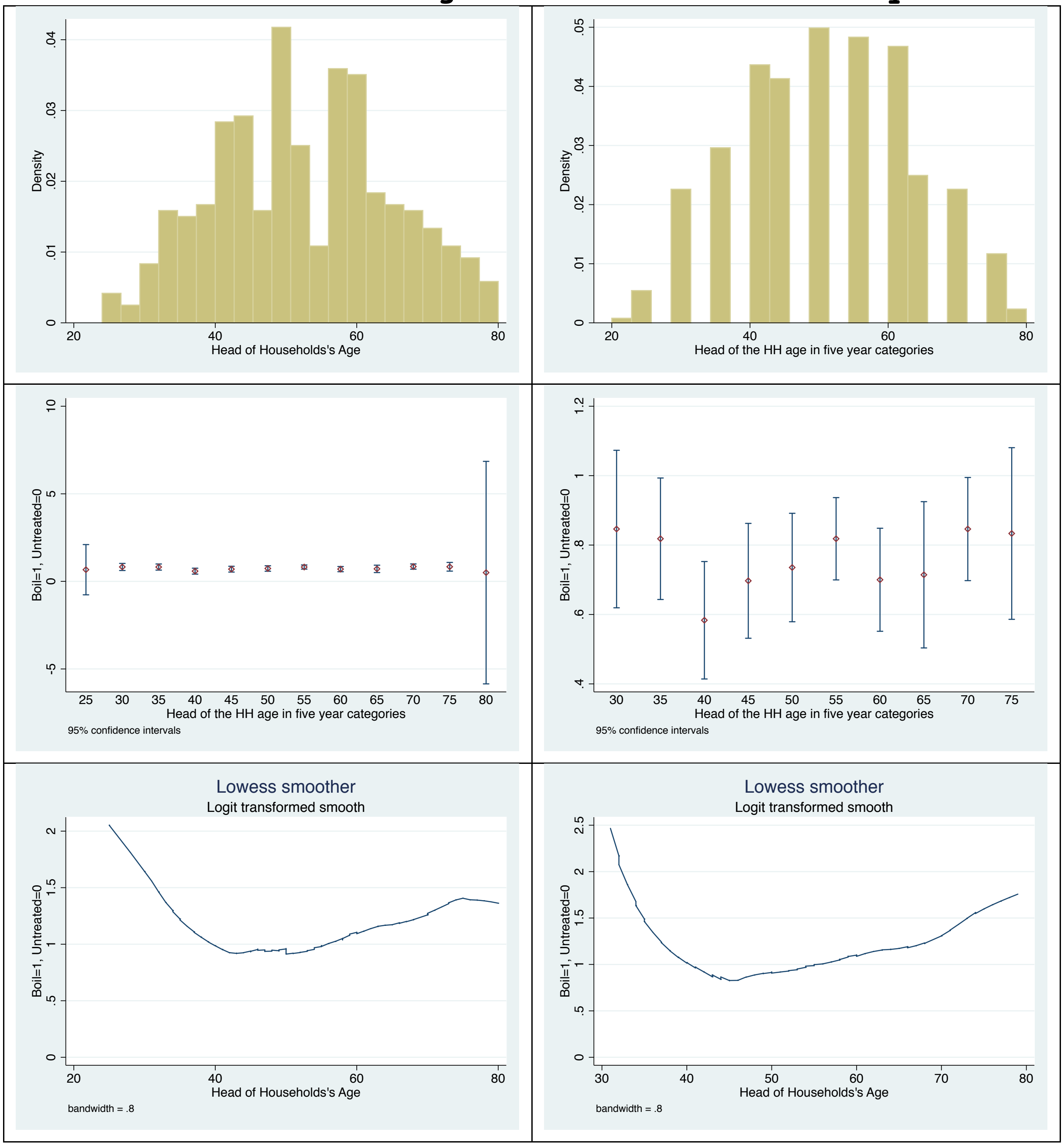
Cross-tab with Q21 for confirmation:

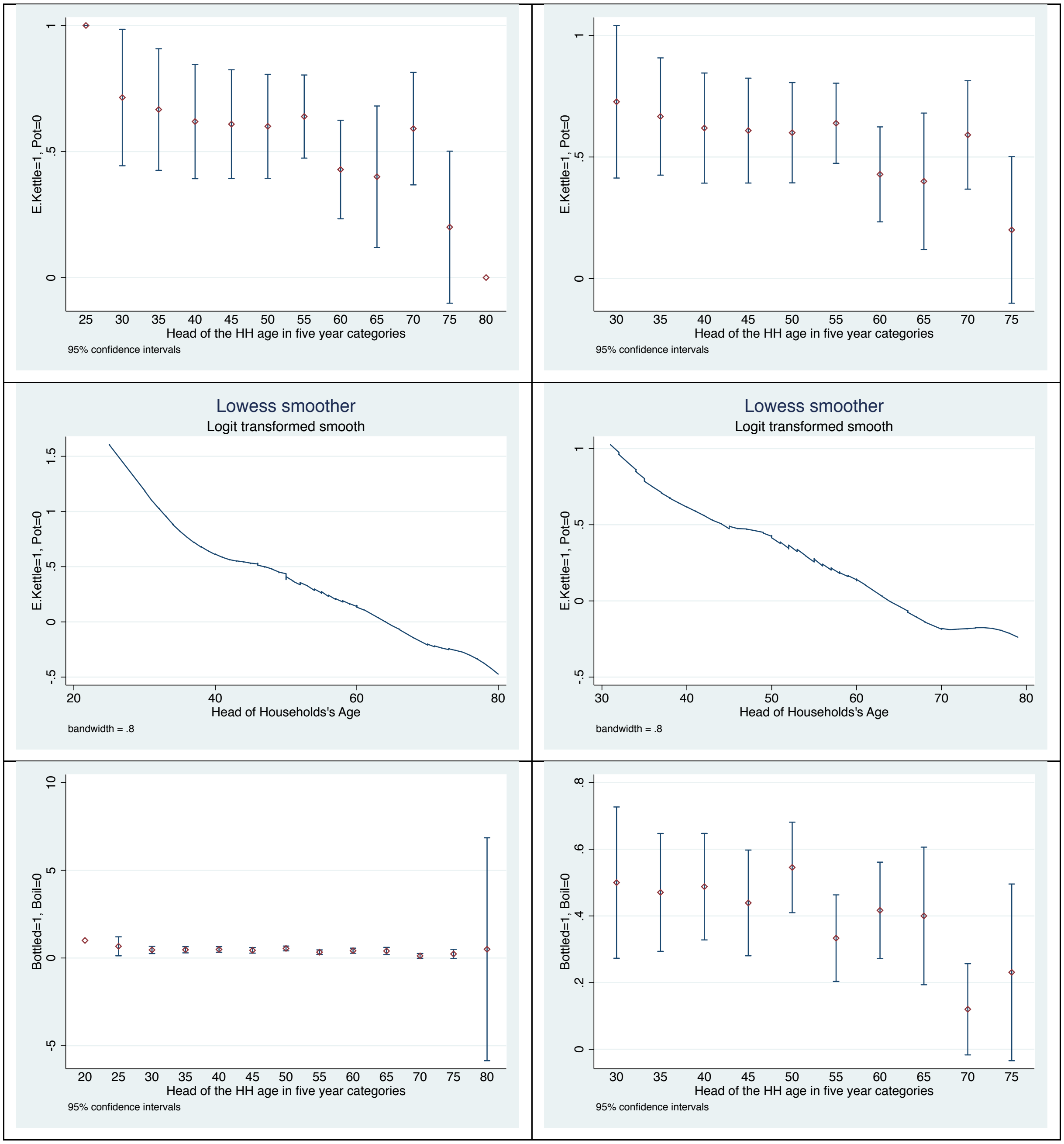
Primary fuel source for cooking (Q21)	Dummy: Safe fuel=1, other=0 Unsafe fu	Safe fuel	.	Total
High-voltage electric	0	8	0	8
Low-voltage electrici	0	238	0	238
Gas fuel [from tank o	0	55	0	55
Liquid fuel [petrol,	22	0	0	22
Coal or charcoal	2	0	0	2
Vegetable or animal b	0	0	1	1
Wood, sawdust, grass	108	0	0	108
Other	0	0	8	8
.m	0	0	8	8
Total	132	301	17	450

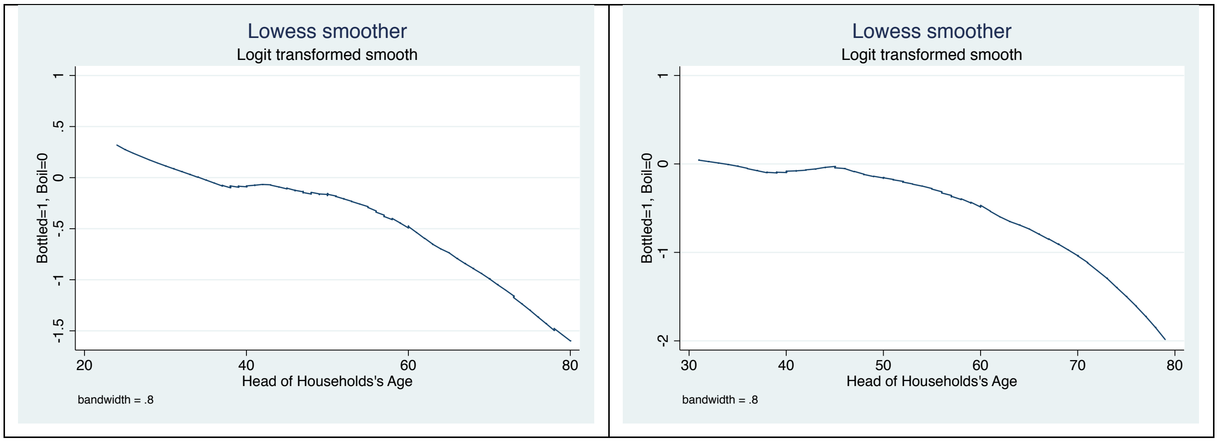
4. Histograms & functional form checks for continuous-variables used in models

This section provides various graphs used for functional form checks to help determined whether some continuous variables needed to be transformed for the three DVs used in the models described in chapters three and four. In some cases, the data range is truncated for visual comparisons, differences may be noted by comparing the axis values across graphs.

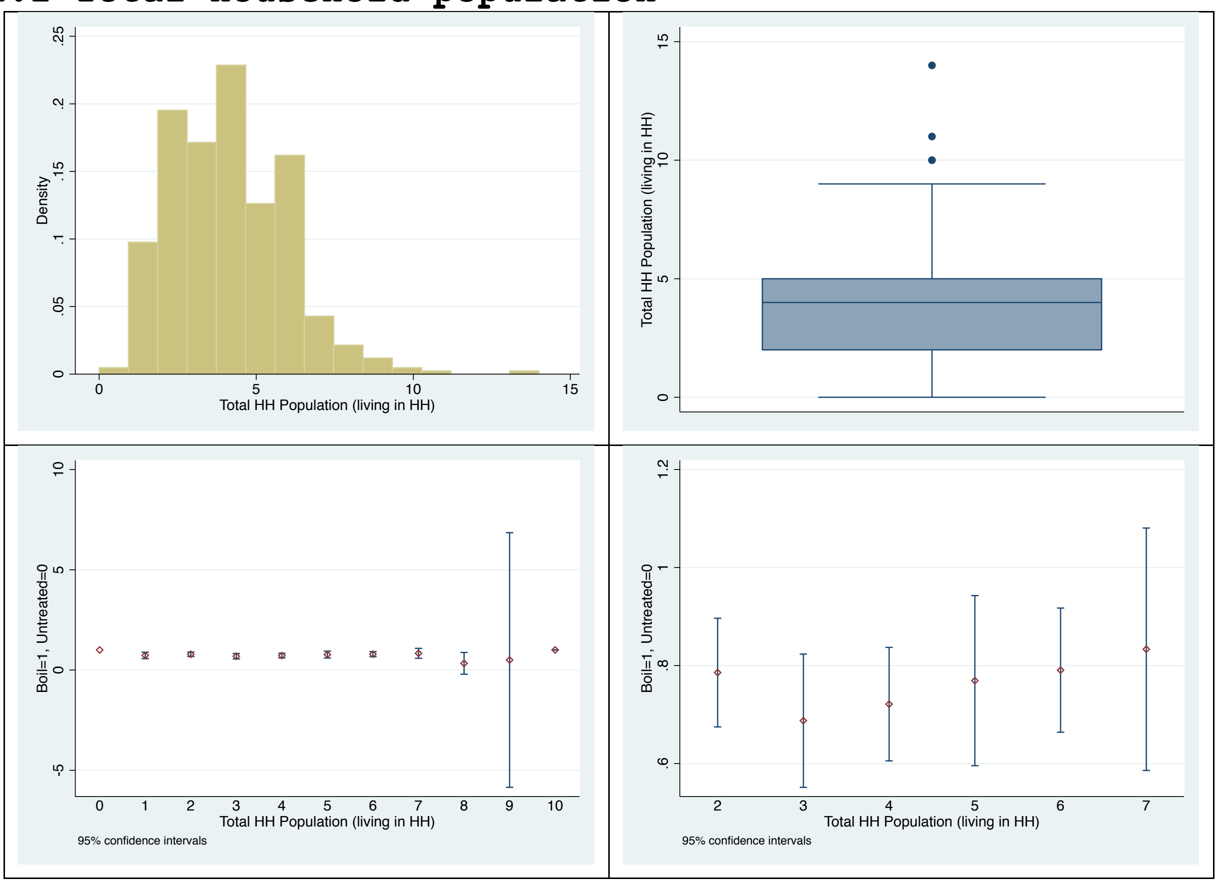
4.1 Head of household age: Transformed with 5-year bins

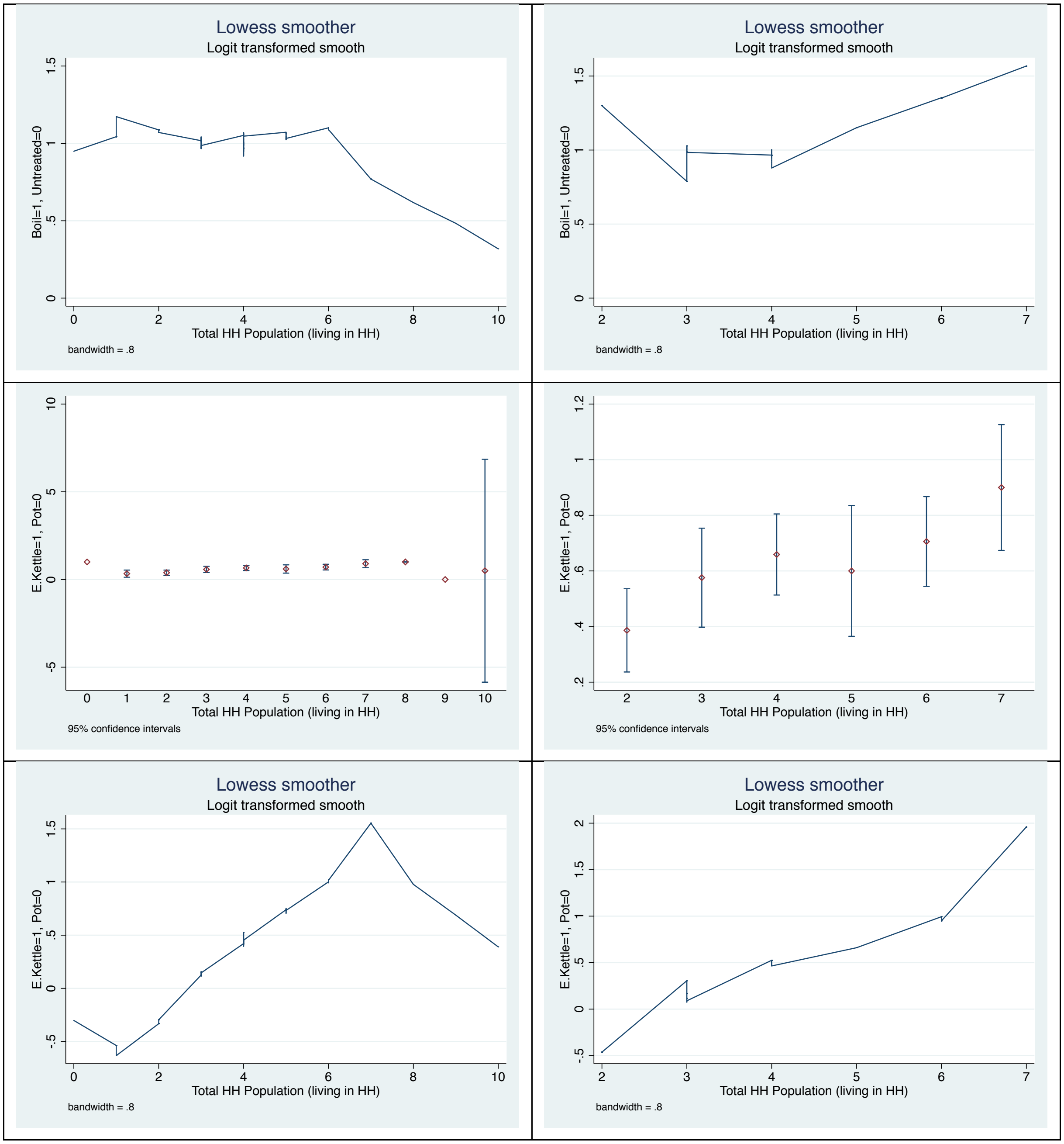


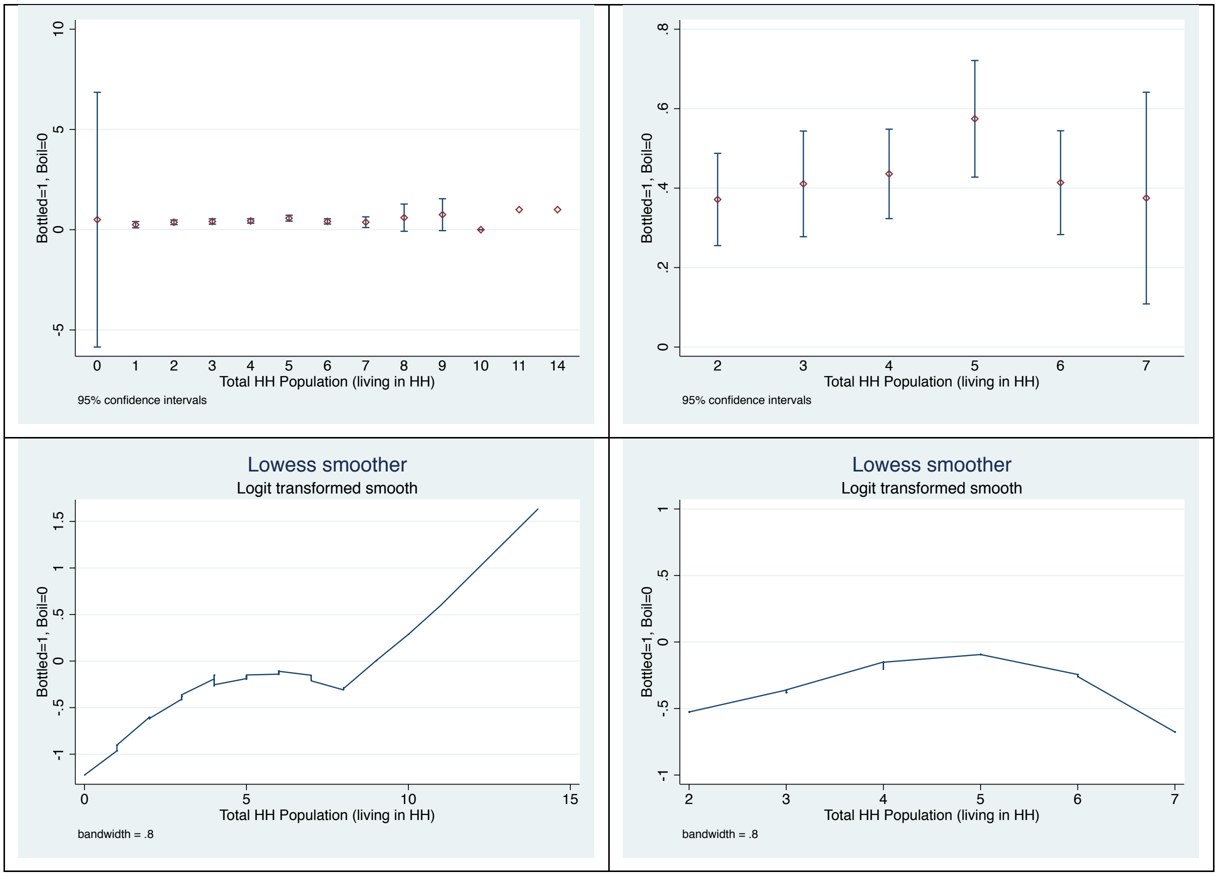

E.Kettle=1, Pot=0
Head of the HH age in five year categories
95% confidence intervals
E.Kettle=1, Pot=0
Head of the HH age in five year categories
95% confidence intervals
Lowess smoother
Logit transformed smooth
E.Kettle=1, Pot=0
Head of Households's Age
bandwidth = .8
Lowess smoother
Logit transformed smooth
E.Kettle=1, Pot=0
Head of Households's Age
bandwidth = .8
Bottled=1, Boil=0
Head of the HH age in five year categories
95% confidence intervals
Bottled=1, Boil=0
Head of the HH age in five year categories
95% confidence intervals



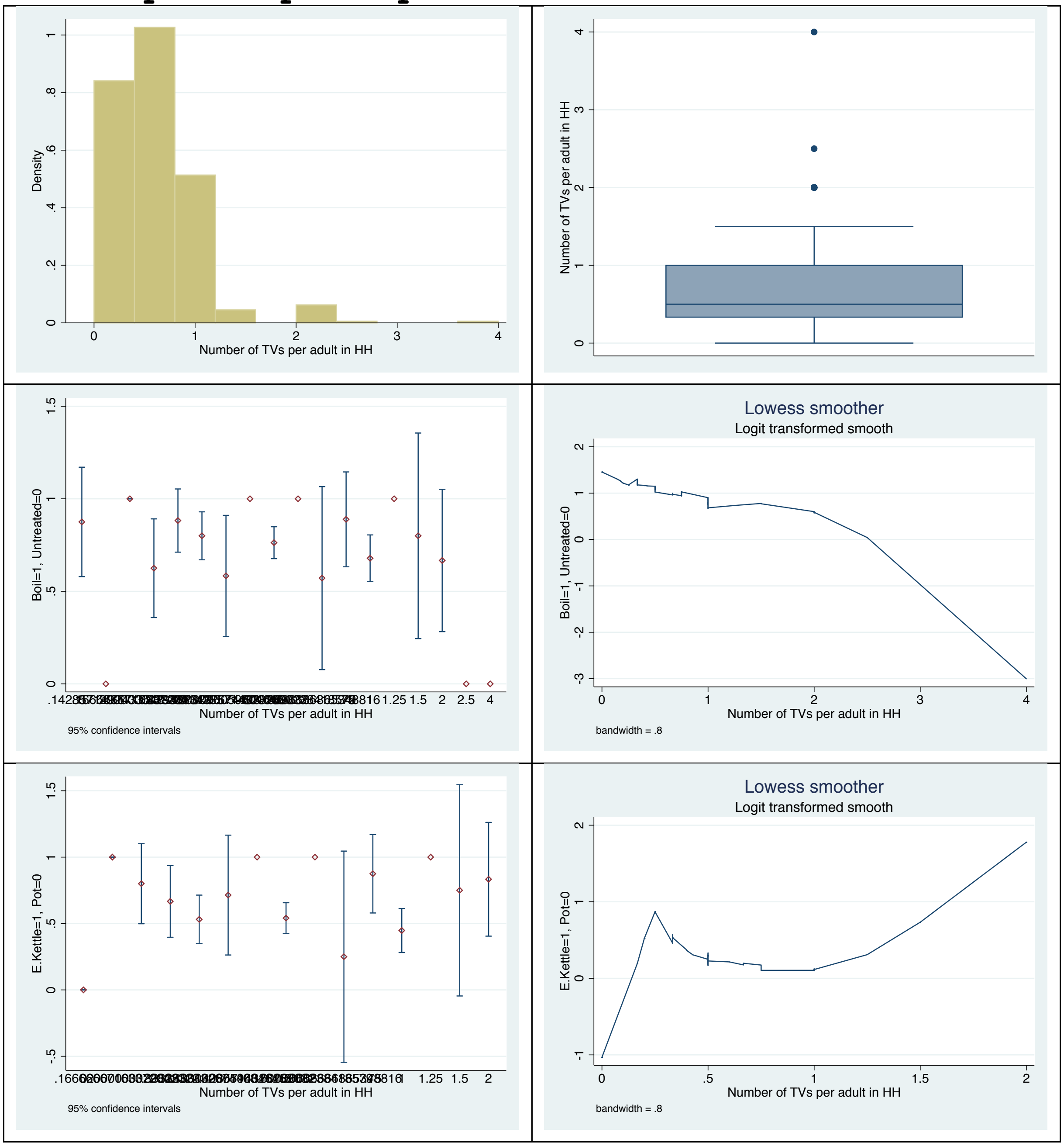
4.2 Total household population

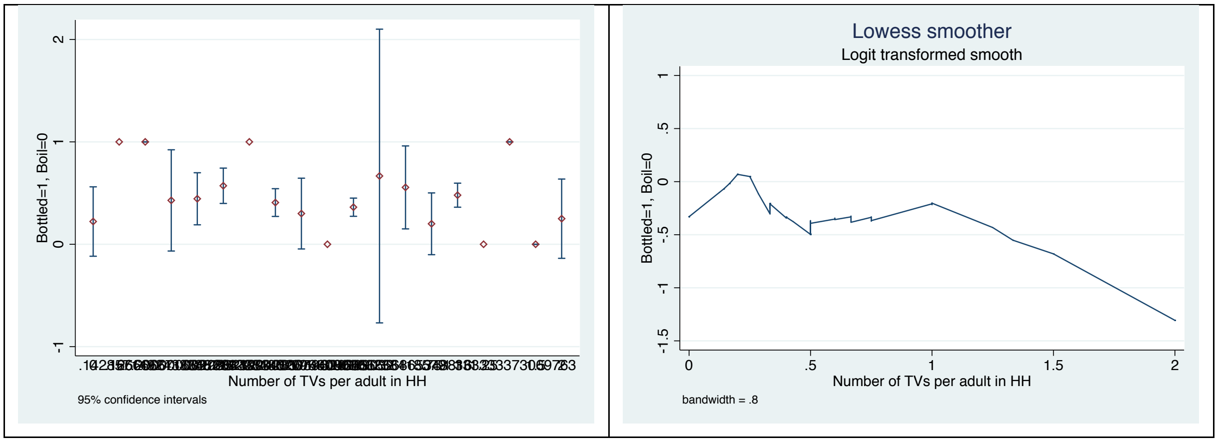



Lowess smoother
Logit transformed smooth
Boil=1, Untreated=0
Total HH Population (living in HH)
bandwidth = .8
Lowess smoother
Logit transformed smooth
Boil=1, Untreated=0
Total HH Population (living in HH)
bandwidth = .8
E.Kettle=1, Pot=0
Total HH Population (living in HH)
95% confidence intervals
E.Kettle=1, Pot=0
Total HH Population (living in HH)
95% confidence intervals
Lowess smoother
Logit transformed smooth
E.Kettle=1, Pot=0
Total HH Population (living in HH)
bandwidth = .8
Lowess smoother
Logit transformed smooth
E.Kettle=1, Pot=0
Total HH Population (living in HH)
bandwidth = .8

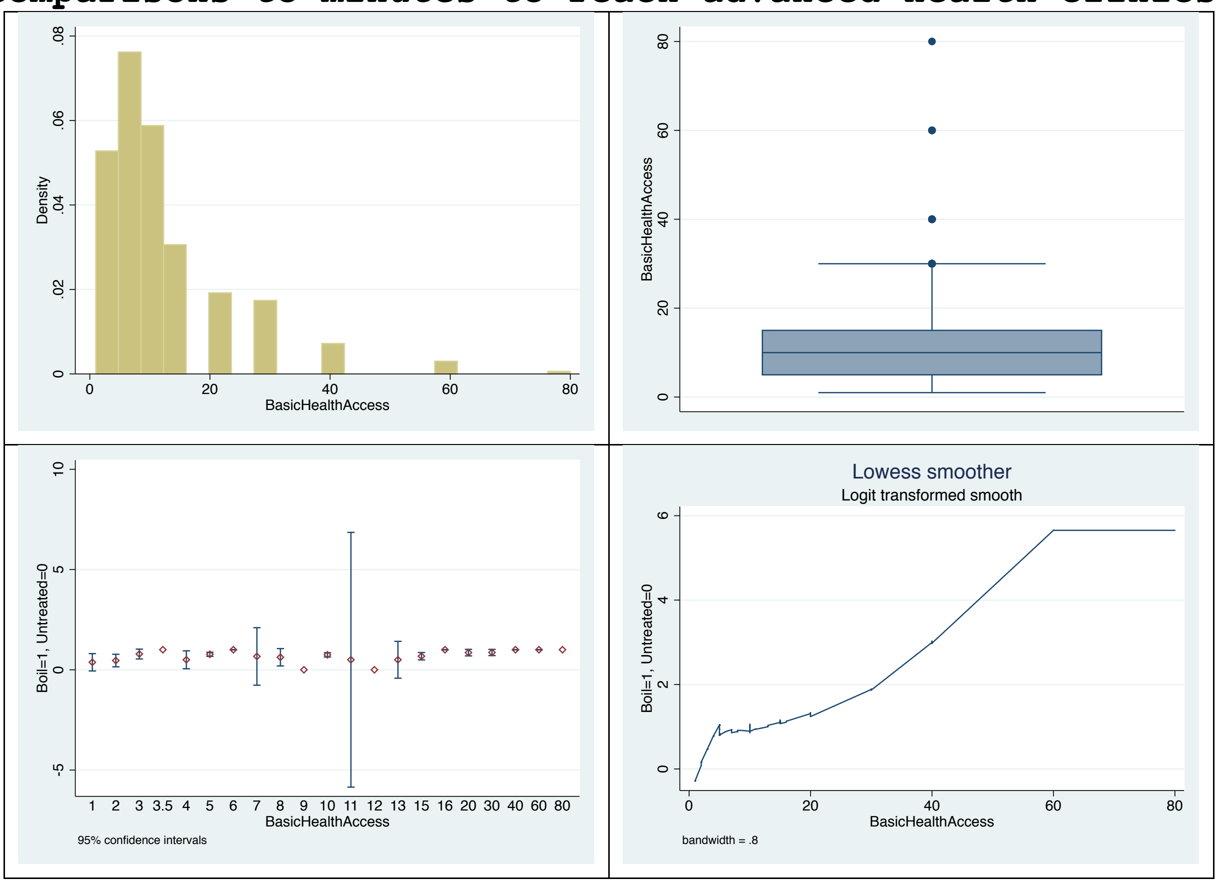

Bottled=1, Boil=0
Total HH Population (living in HH)
95% confidence intervals
Bottled=1, Boil=0
Total HH Population (living in HH)
95% confidence intervals
Lowess smoother
Logit transformed smooth
Bottled=1, Boil=0
Total HH Population (living in HH)
bandwidth = .8
Lowess smoother
Logit transformed smooth
Bottled=1, Boil=0
Total HH Population (living in HH)
bandwidth = .8

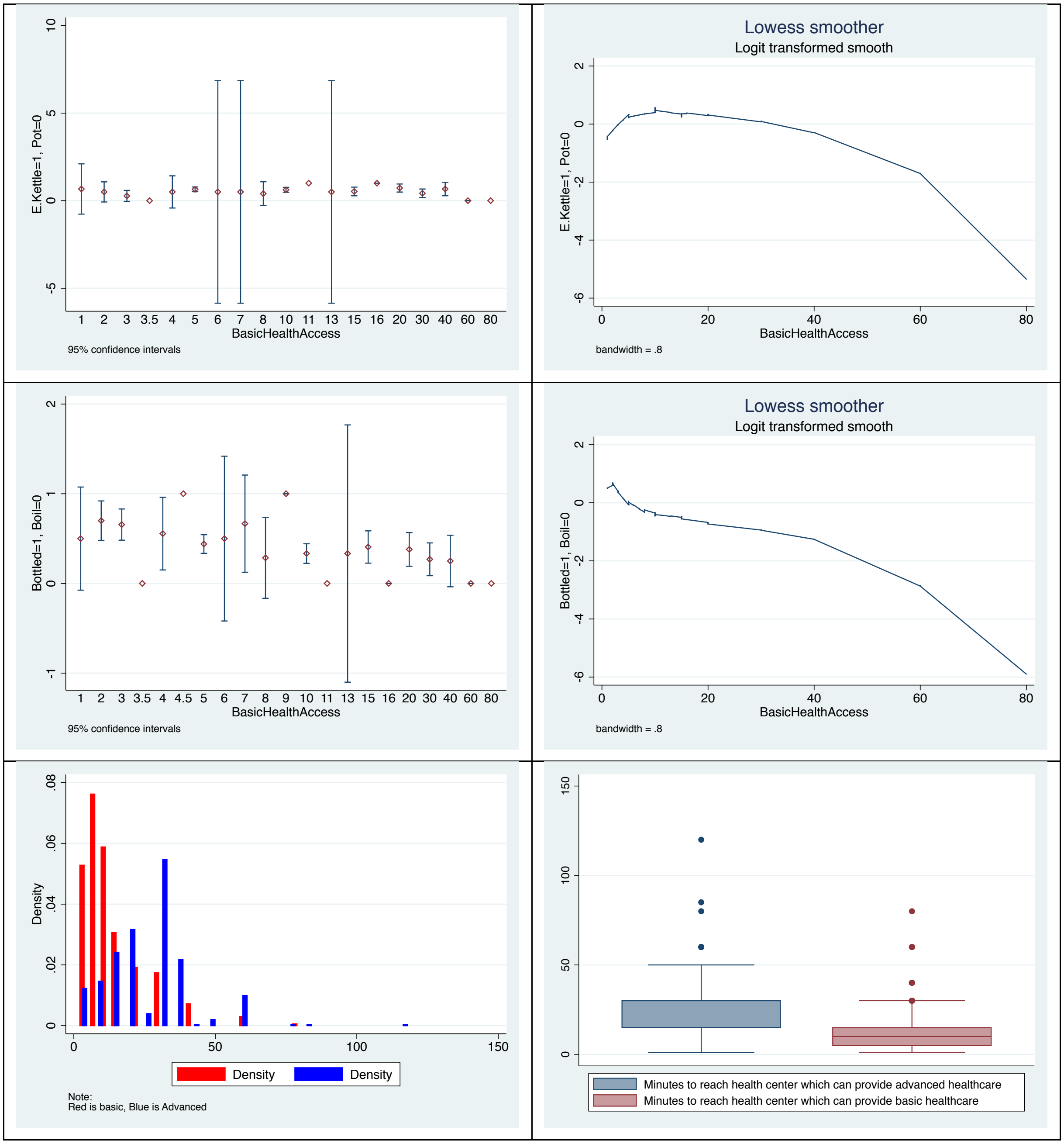
4.3 TVs per HH per capita

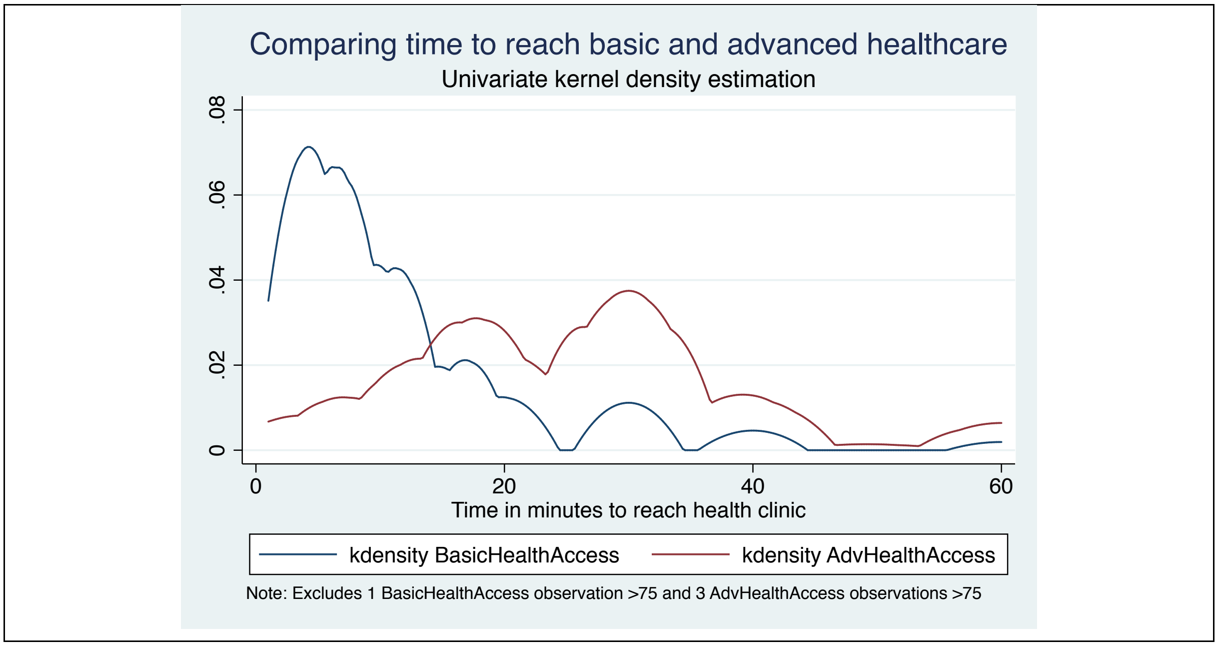




4.4 Time in minutes to reach basic health clinic with comparisons to minutes to reach advanced health clinics




E.Kettle=1, Pot=0
BasicHealthAccess
95% confidence intervals
Lowess smoother
Logit transformed smooth
E.Kettle=1, Pot=0
BasicHealthAccess
bandwidth = .8
Bottled=1, Boil=0
BasicHealthAccess
95% confidence intervals
Lowess smoother
Logit transformed smooth
Bottled=1, Boil=0
BasicHealthAccess
bandwidth = .8
Density
Density
Density
Note:
Red is basic, Blue is Advanced
Minutes to reach health center which can provide advanced healthcare
Minutes to reach health center which can provide basic healthcare



5. Logistic and Multilevel Mixed-Effects Logistic Modeling

5.1.3 Master-list of covariates organized by hierarchical blocks (using Stata variable names)

1. WATER-RELATED

PercWQ_D ImprovedSource_D RelativesBoil_D NeighborsBoil_D

2. ACCESS TO HEALTH SERVICES

BasicHealthAccess AdvHealthAccess AffordProfCare_D

3. ECONOMIC

TVbyHH RMBvillageBottle_r19 HomeDurability_D SafeFuel_D

4. SOCIO-DEMO

head_hh_age HHgender_D Marital_D Literacy_D HHp_total_in

or

head_hh_age Married__F Single__M Single__F Literacy_D HHp_total_in

5. OTHER

Q104e Q104i Q104u Q104s

5.2 Boil/Untreated (BoilUn_D)

5.2.1 Hierarchical blocks in isolation

***WATER-RELATED**

```
Generalized linear models                         No. of obs      =       273
Log pseudolikelihood = -259.1970684               BIC             = -1394.163
                                     (Std. Err. adjusted for 15 clusters in aa3)
---------------------------------------------------------------------------------
                |               Robust
       BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
        PercWQ_D |   .7451367   .0753884    -2.91   0.004     .6111061    .9085636
ImprovedSource_D |   1.107782   .1089833     1.04   0.298     .9135097    1.343369
           _cons |   .7759497   .0777477    -2.53   0.011     .6375965    .9443245
---------------------------------------------------------------------------------
```

Note: too much MD for RelativesBoil_D and NeighborsBoil_D

***ACCESS TO HEALTH SERVICES**

```
Generalized linear models                         No. of obs      =       285
Log pseudolikelihood = -272.0147967               BIC             =  -1464.32
                                      (Std. Err. adjusted for 15 clusters in aa3)
----------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+---------------------------------------------------------------
BasicHealthAccess |   1.004595   .0022663     2.03   0.042     1.000163    1.009047
  AdvHealthAccess |   1.002705   .0021736     1.25   0.213     .9984541    1.006975
 AffordProfCare_D |   .8418414    .040062    -3.62   0.000      .766872    .9241398
            _cons |   .7003068   .0601543    -4.15   0.000     .5917969    .8287128
----------------------------------------------------------------------------------
```

***ACCESS TO HEALTH SERVICES – ADJUSTED (after checking with Wald test)**

```
( 1)  [BoilUn_D]AdvHealthAccess = 0
           chi2(  1) =    1.55
         Prob > chi2 =    0.2127

Generalized linear models                         No. of obs      =       286
Log pseudolikelihood = -273.2331995               BIC             = -1476.179
                                      (Std. Err. adjusted for 15 clusters in aa3)
----------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+---------------------------------------------------------------
BasicHealthAccess |   1.006268   .0016462     3.82   0.000     1.003047      1.0095
 AffordProfCare_D |   .8375365   .0441992    -3.36   0.001     .7552371    .9288041
            _cons |   .7435422   .0483112    -4.56   0.000     .6546352    .8445238
----------------------------------------------------------------------------------
```

***ECONOMIC**

Generalized linear models — No. of obs = 266

Log pseudolikelihood = -254.8646933 — BIC = -1343.147

(Std. Err. adjusted for 15 clusters in aa3)

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
TVbyHH	.8244744	.0918468	-1.73	0.083	.6627549	1.025655
HomeDurability_D	1.007329	.1418935	0.05	0.959	.7643112	1.327616
SafeFuel_D	1.071066	.1339148	0.55	0.583	.838284	1.36849
_cons	.7837688	.1149499	-1.66	0.097	.5879605	1.044787

***SOCIO-DEMO**

Generalized linear models — No. of obs = 278

Log pseudolikelihood = -266.4874342 — BIC = -1409.738

(Std. Err. adjusted for 15 clusters in aa3)

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
head_hh_age	1.001566	.0029375	0.53	0.594	.9958249	1.00734
HHgender_D	.8656973	.1071811	-1.16	0.244	.6791718	1.10345
Marital_D	.9688303	.0898536	-0.34	0.733	.8077995	1.161962
Literacy_D	.8695597	.0718184	-1.69	0.091	.7396004	1.022355
HHp_total_in	1.005165	.0187602	0.28	0.783	.9690604	1.042615
_cons	.8411332	.2016111	-0.72	0.470	.525824	1.345517

***SOCIO-DEMO – WITH INTERACTION TERMS**

Generalized linear models — No. of obs = 278

Log pseudolikelihood = -266.4874316 — BIC = -1404.11

(Std. Err. adjusted for 15 clusters in aa3)

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
head_hh_age	1.001567	.0029471	0.53	0.595	.9958071	1.007359
Married__F	1.155362	.1485295	1.12	0.261	.8980288	1.486434
Single__M	1.032801	.151211	0.22	0.826	.7751634	1.376068
Single__F	1.191912	.1061431	1.97	0.049	1.001019	1.419208
Literacy_D	.8695426	.0710537	-1.71	0.087	.7408596	1.020577
HHp_total_in	1.005173	.0189097	0.27	0.784	.9687852	1.042927
_cons	.7054121	.1583338	-1.55	0.120	.4543451	1.095217

***OTHER**

```
Generalized linear models                          No. of obs      =       276
Log pseudolikelihood = -264.6239005                BIC             = -1405.881
                                   (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------
             |               Robust
    BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Q104e |   1.309144   .2008621     1.76   0.079     .9691418    1.768428
       Q104i |   1.485929   .2493091     2.36   0.018     1.069506    2.064489
       Q104u |   1.380567    .226078     1.97   0.049     1.001537     1.90304
       Q104s |   1.116203    .193271     0.63   0.525      .794982    1.567217
       _cons |   .5909091   .0991759    -3.13   0.002     .4252637    .8210753
------------------------------------------------------------------------------
```

5.2.2 Hierarchical blocks combined in sequence (with adjustments)

***WATER-RELATED + ACCESS TO HEALTH SERVICES**

```
Generalized linear models                          No. of obs      =       269
Log pseudolikelihood = -254.1431433                BIC             = -1358.718
                                        (Std. Err. adjusted for 15 clusters in aa3)
-----------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
        PercWQ_D |   .7792717   .0788371    -2.47   0.014     .6391089    .9501735
 ImprovedSource_D |    1.09265   .0946461     1.02   0.306     .9220393     1.29483
BasicHealthAccess |   1.005011   .0014982     3.35   0.001     1.002079    1.007951
 AffordProfCare_D |   .8957172   .0546549    -1.80   0.071     .7947532    1.009507
            _cons |   .7572438   .0755474    -2.79   0.005      .622751    .9207823
-----------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC**

```
Generalized linear models                          No. of obs      =       252
Log pseudolikelihood = -237.5085236                BIC             = -1243.693
                                        (Std. Err. adjusted for 15 clusters in aa3)
-----------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
         PercWQ_D |   .7932234   .0820249    -2.24   0.025      .647702    .9714397
 ImprovedSource_D |   1.085536   .0852674     1.04   0.296     .9306441    1.266208
BasicHealthAccess |   1.005336   .0016369     3.27   0.001     1.002133     1.00855
 AffordProfCare_D |   .9097319   .0654334    -1.32   0.188     .7901142    1.047459
           TVbyHH |   .8579605   .0875325    -1.50   0.133     .7024645    1.047877
 HomeDurability_D |   1.107236   .1862905     0.61   0.545     .7962086    1.539761
            _cons |   .7434929   .1372767    -1.61   0.108     .5177416    1.067679
-----------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO**

```
Generalized linear models                         No. of obs      =        246
Log pseudolikelihood = -230.8177537               BIC             = -1175.107
                                      (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |   .7764817   .0746212    -2.63   0.008     .6431753    .9374176
 ImprovedSource_D |   1.098537   .0907228     1.14   0.255     .9343687     1.29155
BasicHealthAccess |   1.004957   .0017159     2.90   0.004     1.001599    1.008326
 AffordProfCare_D |   .9095837    .063241    -1.36   0.173      .793708    1.042376
           TVbyHH |   .8295954   .0872503    -1.78   0.076     .6750621    1.019504
 HomeDurability_D |   1.119819   .1889036     0.67   0.502     .8045584    1.558612
      head_hh_age |   1.003222   .0034342     0.94   0.347     .9965137    1.009976
       Married__F |   1.083202   .1207362     0.72   0.473     .8706277    1.347678
        Single__M |   .9498115   .1362687    -0.36   0.720     .7169952    1.258226
        Single__F |   1.360085   .1365668     3.06   0.002     1.117111    1.655906
       Literacy_D |   1.054114   .0948139     0.59   0.558     .8837409    1.257333
      HHp_total_in |   .9970423   .0155013    -0.19   0.849     .9671187    1.027892
            _cons |   .6058549   .1815769    -1.67   0.095     .3367134    1.090126
------------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO + OTHER**

```
Generalized linear models                         No. of obs      =        235
Log pseudolikelihood = -218.9383836               BIC             = -1106.692
                                      (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
         BoilUn_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |   .7388264   .0858592    -2.60   0.009      .588334    .9278137
 ImprovedSource_D |   1.093352   .1046043     0.93   0.351     .9064062    1.318855
BasicHealthAccess |   1.003832   .0019324     1.99   0.047     1.000052    1.007626
 AffordProfCare_D |   .8853976     .06789    -1.59   0.112     .7618516    1.028979
           TVbyHH |   .7794778   .0893675    -2.17   0.030     .6226057    .9758755
 HomeDurability_D |    1.19359   .1932909     1.09   0.274     .8689821    1.639454
      head_hh_age |   1.002649   .0039553     0.67   0.502      .994927    1.010432
       Married__F |   1.036184   .1203662     0.31   0.760     .8251991    1.301113
        Single__M |   1.060944   .1666359     0.38   0.706     .7798291    1.443396
        Single__F |   1.338637   .1718041     2.27   0.023      1.04092    1.721504
       Literacy_D |   1.031098   .0865319     0.36   0.715     .8747129    1.215443
     HHp_total_in |   .9923791   .0152891    -0.50   0.620      .962861    1.022802
            Q104e |   1.220483   .2179402     1.12   0.265     .8600696    1.731927
            Q104i |   1.465871   .3116887     1.80   0.072     .9662837    2.223756
            Q104u |    1.60185   .3673575     2.05   0.040     1.021911    2.510908
            Q104s |    1.49723   .4310039     1.40   0.161     .8516386    2.632218
            _cons |   .5017021   .2179385    -1.59   0.112     .2141339    1.175456
------------------------------------------------------------------------------------
```

5.2.3 Final Model

```
Generalized linear models                          No. of obs      =        246
Optimization     : ML                              Residual df     =        233
                                                   Scale parameter =          1
Deviance         =  107.6355074                    (1/df) Deviance =    .461955
Pearson          =  68.61648678                    (1/df) Pearson  =   .2944914

Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =   1.982258
Log pseudolikelihood = -230.8177537                BIC             =  -1175.107
                                   (Std. Err. adjusted for 15 clusters in aa3)
```

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.7764817	.0746212	-2.63	0.008	.6431753	.9374176
ImprovedSource_D	1.098537	.0907228	1.14	0.255	.9343687	1.29155
BasicHealthAccess	1.004957	.0017159	2.90	0.004	1.001599	1.008326
AffordProfCare_D	.9095837	.063241	-1.36	0.173	.793708	1.042376
TVbyHH	.8295954	.0872503	-1.78	0.076	.6750621	1.019504
HomeDurability_D	1.119819	.1889036	0.67	0.502	.8045584	1.558612
head_hh_age	1.003222	.0034342	0.94	0.347	.9965137	1.009976
Married__F	1.083202	.1207362	0.72	0.473	.8706277	1.347678
Single__M	.9498115	.1362687	-0.36	0.720	.7169952	1.258226
Single__F	1.360085	.1365668	3.06	0.002	1.117111	1.655906
Literacy_D	1.054114	.0948139	0.59	0.558	.8837409	1.257333
HHp_total_in	.9970423	.0155013	-0.19	0.849	.9671187	1.027892
_cons	.6058549	.1815769	-1.67	0.095	.3367134	1.090126

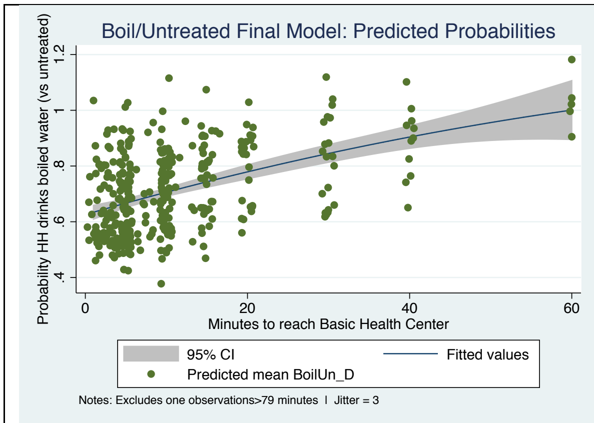
5.2.4 Final Model – Diagnostics & graphs

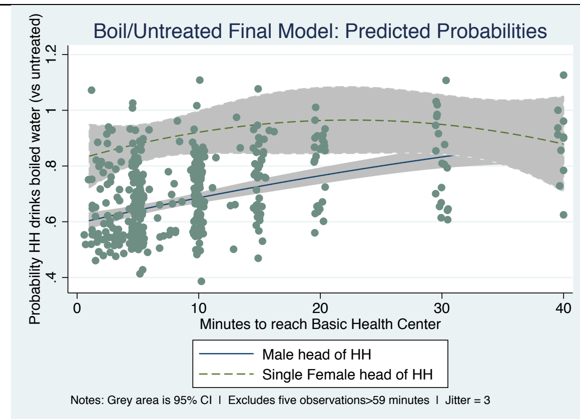
Boil=1, Untreated= 0	esample() from estimates store 0	1	Total
Untreated	6	69	75
Boil	38	177	215

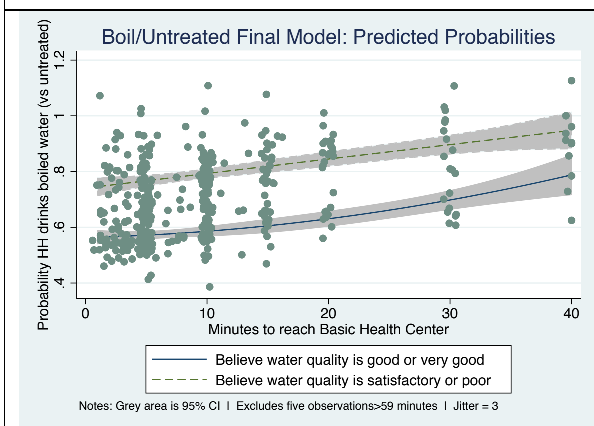
```
Predictive margins                              Number of obs   =        246
Model VCE    : Robust
Expression   : Predicted mean BoilUn_D, predict()
```

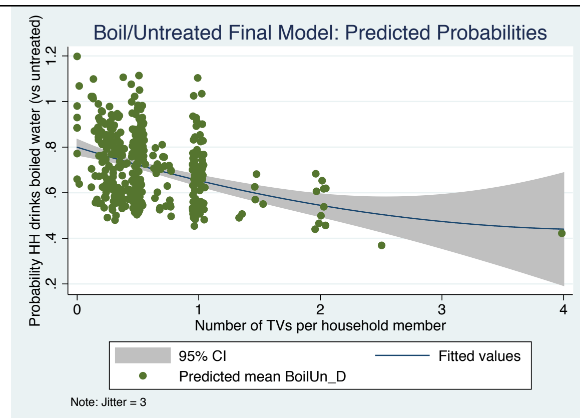
	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.7195122	.0371568	19.36	0.000	.6466862	.7923382

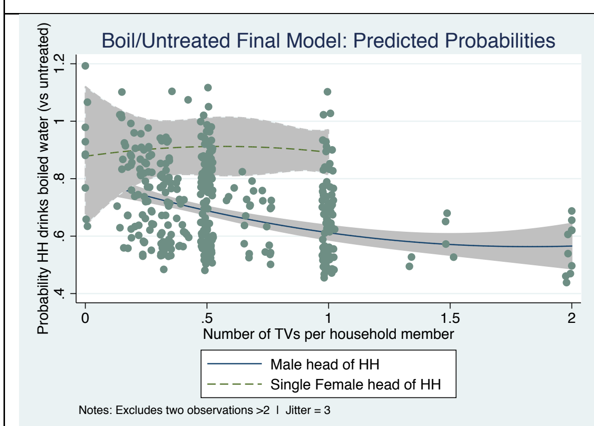
Note: Other graphs provided in chapter three.

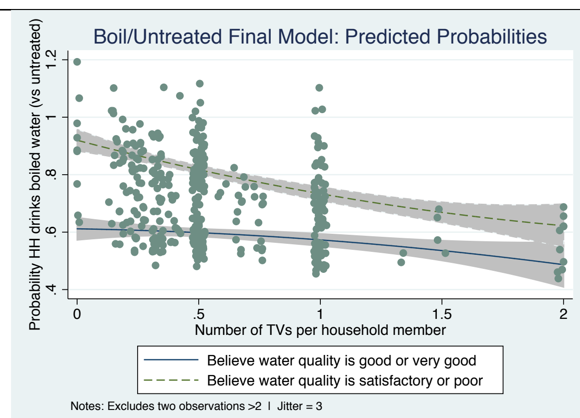








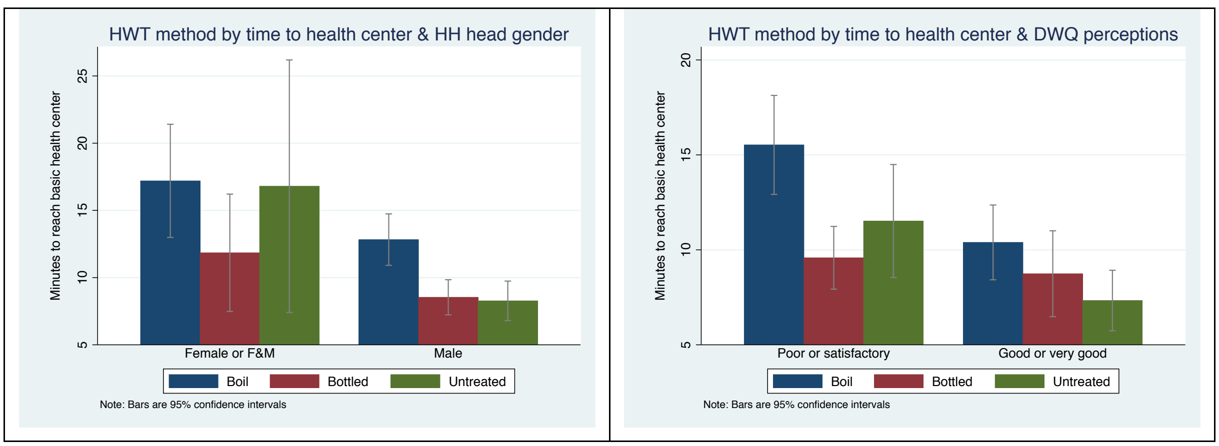




5.2.5 Related analyses

. cs BoilUn_D HHgender_D, or

```
                 | Dummy: Male=1, other=0 |
                 |   Exposed   Unexposed  |      Total
-----------------+------------------------+------------
           Cases |       172          42  |        214
        Noncases |        70           5  |         75
-----------------+------------------------+------------
           Total |       242          47  |        289
                 |                        |
            Risk |  .7107438     .893617  |   .7404844
                 |                        |
                 |      Point estimate    |    [95% Conf. Interval]
                 |------------------------+------------------------
 Risk difference |        -.1828732       |   -.2879135   -.0778329
      Risk ratio |         .7953562       |    .7003278    .9032791
 Prev. frac. ex. |         .2046438       |    .0967209    .2996722
 Prev. frac. pop |         .1713627       |
      Odds ratio |          .292517       |    .1148176    .7480839 (Cornfield)
                 +-------------------------------------------------
                               chi2(1) =     6.85  Pr>chi2 = 0.0089
```



5.2.6 Sensitivity analyses

***Bootstrapping (1,000 reps) to see impact on SE estimates**

```
Generalized linear models                          No. of obs      =        246
Log pseudolikelihood = -230.8177537                BIC             = -1175.107
                                         (Replications based on 15 clusters in aa3)
----------------------------------------------------------------------------------
                  |   Observed   Bootstrap                         Normal-based
        BoilUn_D  |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+---------------------------------------------------------------
         PercWQ_D |   .7764817   .0833379    -2.36   0.018     .6291784     .9582717
 ImprovedSource_D |   1.098537   .1088641     0.95   0.343     .9046102     1.334038
```

BasicHealthAccess	1.004957	.0028986	1.71	0.086	.9992918	1.010654
AffordProfCare_D	.9095837	.0677015	-1.27	0.203	.786116	1.052443
TVbyHH	.8295954	.0952806	-1.63	0.104	.6623755	1.039031
HomeDurability_D	1.119819	.2104428	0.60	0.547	.7747919	1.618491
head_hh_age	1.003222	.0033595	0.96	0.337	.9966591	1.009828
Married__F	1.083202	.137793	0.63	0.530	.844168	1.38992
Single__M	.9498115	.6698897	-0.07	0.942	.2383944	3.784241
Single__F	1.360085	.1535154	2.72	0.006	1.090158	1.696848
Literacy_D	1.054114	.1013654	0.55	0.584	.8730409	1.272743
HHp_total_in	.9970423	.0174609	-0.17	0.866	.9634003	1.031859
_cons	.6058549	.1865551	-1.63	0.104	.3313342	1.107824

Note: One or more parameters could not be estimated in 1 bootstrap replicate;
standard-error estimates include only complete replications.

***Full model**

Generalized linear models — No. of obs = 241

Log pseudolikelihood = -224.9000559 — BIC = -1139.249

(Std. Err. adjusted for 15 clusters in aa3)

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.7814129	.077001	-2.50	0.012	.6441731	.9478915
ImprovedSource_D	1.069762	.095916	0.75	0.452	.8973619	1.275284
BasicHealthAccess	1.002399	.0024873	0.97	0.334	.9975359	1.007286
AdvHealthAccess	1.004947	.0034799	1.43	0.154	.9981496	1.011791
AffordProfCare_D	.8920298	.059381	-1.72	0.086	.782918	1.016348
TVbyHH	.7928068	.0892338	-2.06	0.039	.6358593	.9884933
HomeDurability_D	1.101605	.1763388	0.60	0.545	.8049524	1.507584
SafeFuel_D	1.196722	.1362387	1.58	0.115	.9573914	1.49588
head_hh_age	1.003698	.0034784	1.07	0.287	.9969034	1.010539
Married__F	1.133738	.1015584	1.40	0.161	.9511816	1.351332
Single__M	.9743143	.1449373	-0.17	0.861	.7279068	1.304134
Single__F	1.362018	.1404983	3.00	0.003	1.112698	1.667202
Literacy_D	1.054873	.0935599	0.60	0.547	.8865531	1.255151
HHp_total_in	.9896806	.013714	-0.75	0.454	.9631633	1.016928
_cons	.5113773	.1828691	-1.88	0.061	.2537178	1.0307

***No adjustment for clusters, just robust SE**

Generalized linear models — No. of obs = 246

Log pseudolikelihood = -230.8177537 — BIC = -1175.107

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.7764817	.0776478	-2.53	0.011	.6382803	.9446067

ImprovedSource_D	1.098537	.0933618	1.11	0.269	.9299797	1.297646
BasicHealthAccess	1.004957	.0019255	2.58	0.010	1.00119	1.008738
AffordProfCare_D	.9095837	.0760021	-1.13	0.257	.7721804	1.071437
TVbyHH	.8295954	.0951378	-1.63	0.103	.6625989	1.03868
HomeDurability_D	1.119819	.1757834	0.72	0.471	.8232477	1.523228
head_hh_age	1.003222	.0032244	1.00	0.317	.9969222	1.009562
Married__F	1.083202	.0959135	0.90	0.367	.9106231	1.288487
Single__M	.9498115	.1883059	-0.26	0.795	.6439936	1.400855
Single__F	1.360085	.1493443	2.80	0.005	1.09673	1.686679
Literacy_D	1.054114	.0832956	0.67	0.505	.9028717	1.230691
HHp_total_in	.9970423	.0211237	-0.14	0.889	.9564886	1.039316
_cons	.6058549	.1877142	-1.62	0.106	.3300941	1.111986

*No adjustment for clusters, just robust SE – Bootstrap with 1,000 reps

```
Generalized linear models                          No. of obs      =        246
Log pseudolikelihood = -230.8177537                BIC             = -1175.107
```

BoilUn_D	Observed IRR	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
PercWQ_D	.7764817	.0786837	-2.50	0.013	.6366136	.9470796
ImprovedSource_D	1.098537	.0978536	1.06	0.291	.9225565	1.308087
BasicHealthAccess	1.004957	.0021662	2.29	0.022	1.00072	1.009212
AffordProfCare_D	.9095837	.0795647	-1.08	0.279	.7662754	1.079693
TVbyHH	.8295954	.1047314	-1.48	0.139	.6477498	1.062491
HomeDurability_D	1.119819	.1928901	0.66	0.511	.7989641	1.569525
head_hh_age	1.003222	.0033146	0.97	0.330	.9967465	1.00974
Married__F	1.083202	.1060718	0.82	0.414	.894038	1.312389
Single__M	.9498115	.4241281	-0.12	0.908	.3958609	2.278937
Single__F	1.360085	.165318	2.53	0.011	1.071773	1.725955
Literacy_D	1.054114	.0902834	0.62	0.538	.8912168	1.246786
HHp_total_in	.9970423	.0224593	-0.13	0.895	.9539805	1.042048
_cons	.6058549	.2009264	-1.51	0.131	.3162826	1.160545

*Adjust for county-clusters only

```
Generalized linear models                          No. of obs      =        246
Log pseudolikelihood = -230.8177537                BIC             = -1241.171
                                        (Std. Err. adjusted for 2 clusters in aa1)
```

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.7764817	.011561	-16.99	0.000	.7541499	.7994747
ImprovedSource_D	1.098537	.1450256	0.71	0.477	.8480897	1.422944
BasicHealthAccess	1.004957	.0017792	2.79	0.005	1.001476	1.00845
AffordProfCare_D	.9095837	.0589127	-1.46	0.143	.8011453	1.0327

```
           TVbyHH |   .8295954   .1130807    -1.37   0.171     .6350978    1.083658
 HomeDurability_D |   1.119819   .1240746     1.02   0.307       .90123    1.391425
      head_hh_age |   1.003222   .0052775     0.61   0.541     .9929314    1.013619
       Married__F |   1.083202   .1187796     0.73   0.466     .8737155    1.342916
        Single__M |   .9498115   .0296374    -1.65   0.099      .893464    1.009713
        Single__F |   1.360085   .3359684     1.25   0.213     .8381121    2.207141
       Literacy_D |   1.054114   .0226928     2.45   0.014     1.010562    1.099543
     HHp_total_in |   .9970423   .0090312    -0.33   0.744     .9794977    1.014901
            _cons |   .6058549   .1147724    -2.65   0.008      .417944    .8782519
------------------------------------------------------------------------------------
```

***Compared to mixed effects multilevel logit with OR**

```
Mixed-effects logistic regression               Number of obs      =       246
Group variable:             aa3                 Number of groups   =        15

                                                Obs per group: min =         5
                                                               avg =      16.4
                                                               max =        29

Integration method: mvaghermite                 Integration points =        15

                                                Wald chi2(12)      =     21.21
Log likelihood = -124.36723                     Prob > chi2        =    0.0474
------------------------------------------------------------------------------------
        BoilUn_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
        PercWQ_D |   .4014895   .1580532    -2.32   0.020     .1856026    .8684887
ImprovedSource_D |   1.884791   .8715936     1.37   0.170     .7614438    4.665398
BasicHealthAccess|   1.058654   .0314827     1.92   0.055      .998713    1.122193
 AffordProfCare_D|   .7637139   .3152666    -0.65   0.514     .3400545    1.715192
          TVbyHH |   .5381037   .1861663    -1.79   0.073     .2731354    1.060117
HomeDurability_D |    2.21091   1.399173     1.25   0.210     .6395708    7.642816
     head_hh_age |   1.010889   .0145073     0.75   0.450     .9828508    1.039726
      Married__F |   2.034773   1.557767     0.93   0.353     .4537945    9.123736
       Single__M |   .5819331    .496318    -0.63   0.526     .1093709    3.096309
       Single__F |   8.886908   10.76879     1.80   0.071     .8266076    95.54368
      Literacy_D |   1.425106   .6288263     0.80   0.422     .6001442    3.384066
    HHp_total_in |   .9750577    .087285    -0.28   0.778     .8181494    1.162059
           _cons |   .7251349   .8943954    -0.26   0.794     .0646443    8.134056
-----------------+------------------------------------------------------------------
aa3              |
       var(_cons)|   .8671759   .6176049                      .2147234    3.502153
------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =     8.34 Prob>=chibar2 = 0.0019
```

***Compared to single level logit with OR**

```
Logistic regression                                 Number of obs   =        246
                                                    LR chi2(12)     =      34.89
                                                    Prob > chi2     =     0.0005
Log likelihood = -128.53719                         Pseudo R2       =     0.1195
```

BoilUn_D	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.3847812	.1364849	-2.69	0.007	.1919933	.7711549
ImprovedSource_D	1.235055	.4169533	0.63	0.532	.637267	2.393597
BasicHealthAccess	1.036091	.0220407	1.67	0.096	.9937798	1.080203
AffordProfCare_D	.660324	.2418592	-1.13	0.257	.3220954	1.353723
TVbyHH	.5189571	.1715735	-1.98	0.047	.2714651	.9920851
HomeDurability_D	1.778348	.984755	1.04	0.299	.6007122	5.264621
head_hh_age	1.015443	.0135528	1.15	0.251	.9892249	1.042357
Married__F	1.480188	.9281758	0.63	0.532	.433069	5.059138
Single__M	.7137908	.550706	-0.44	0.662	.1573437	3.238117
Single__F	5.728266	6.390226	1.56	0.118	.6433639	51.00229
Literacy_D	1.302963	.5154424	0.67	0.504	.600072	2.829183
HHp_total_in	.9886129	.0826671	-0.14	0.891	.839169	1.164671
_cons	1.081174	1.174817	0.07	0.943	.1285199	9.095387

***Final model with RelativesBoil_D**

```
Generalized linear models                            No. of obs      =       146
Log pseudolikelihood = -139.0832964                  BIC             = -613.6695
                                        (Std. Err. adjusted for 15 clusters in aa3)
```

BoilUn_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.9505042	.1209638	-0.40	0.690	.7406751	1.219777
ImprovedSource_D	1.105686	.0636504	1.75	0.081	.9877138	1.237749
BasicHealthAccess	1.002779	.0017115	1.63	0.104	.9994298	1.006139
AffordProfCare_D	.957908	.0760787	-0.54	0.588	.8198227	1.119251
TVbyHH	.8545376	.0874116	-1.54	0.124	.6992956	1.044243
HomeDurability_D	1.192771	.2650782	0.79	0.428	.7715931	1.843851
head_hh_age	1.001462	.0022805	0.64	0.521	.9970019	1.005941
Married__F	1.042318	.1032611	0.42	0.676	.8583665	1.265691
Single__M	1.273005	.1104216	2.78	0.005	1.07398	1.508913
Single__F	1.33088	.1616278	2.35	0.019	1.048975	1.688544
Literacy_D	1.027936	.0619068	0.46	0.647	.9134886	1.156723
HHp_total_in	1.006871	.0224358	0.31	0.759	.9638444	1.051819
RelativesBoil_D	1.480905	.1938258	3.00	0.003	1.145827	1.91397
_cons	.4799086	.2058975	-1.71	0.087	.2069967	1.112637

5.3 Kettle/Pot (KettlePot_D)

5.3.1 Hierarchical blocks in isolation

***WATER-RELATED**

```
Generalized linear models                          No. of obs      =       120
Log pseudolikelihood =  -105.675642                BIC             = -477.2103
                                       (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                 |               Robust
     KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
       PercWQ_D |   1.306353   .2342425     1.49   0.136     .9192448    1.856477
ImprovedSource_D |   1.039677   .3040754     0.13   0.894     .5860658    1.844379
 RelativesBoil_D |   .8920192   .3445913    -0.30   0.767     .4183607    1.901943
 NeighborsBoil_D |   .7977265    .345045    -0.52   0.601     .3417269    1.862211
           _cons |   .6414063   .1485311    -1.92   0.055     .4073987    1.009827
------------------------------------------------------------------------------------
```

EXAMINING CAUSE OF SO MUCH MISSING DATA

```
                |   Dummy: Good, very
                |        good=1
    KettlePot_D | Poor or s  Good or v |     Total
----------------+----------------------+----------
      Boil: Pot |        62         25 |        87
Boil: E. Kettle |        67         47 |       114

                |  Dummy: Improved=1,
                |     Unimproved=0
    KettlePot_D | Unimprove  Improved  |     Total
----------------+----------------------+----------
      Boil: Pot |        39         52 |        91
Boil: E. Kettle |        54         68 |       122

                |  Dummy: Most or all
                |        boil=1
    KettlePot_D | None, som  Most or a |     Total
----------------+----------------------+----------
      Boil: Pot |        15         47 |        62
Boil: E. Kettle |        34         42 |        76

                |  Dummy: Most or all
                |        boil=1
    KettlePot_D | None, som  Most or a |     Total
----------------+----------------------+----------
      Boil: Pot |        15         46 |        61
Boil: E. Kettle |        35         42 |        77
```

***WATER-RELATED – ADJUSTED (due to missing data from two variables)**

```
Generalized linear models                         No. of obs      =       199
Log pseudolikelihood = -176.8882733               BIC             = -911.7112
                                        (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                 |               Robust
     KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------------
        PercWQ_D |   1.230788    .264904     0.96   0.335     .8071943    1.876672
ImprovedSource_D |   .9820873   .2608589    -0.07   0.946     .5835212    1.652889
           _cons |   .5339606   .1613107    -2.08   0.038     .2953652     .965293
------------------------------------------------------------------------------------
```

***ACCESS TO HEALTH SERVICES**

```
Generalized linear models                         No. of obs      =       210
Log pseudolikelihood = -185.1450449               BIC             = -967.2141
                                        (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+------------------------------------------------------------------
BasicHealthAccess |   .9927028   .0125403    -0.58   0.562     .9684261    1.017588
  AdvHealthAccess |   .9977076   .0045206    -0.51   0.612     .9888866    1.006607
 AffordProfCare_D |    1.06029   .1656043     0.37   0.708     .7806874    1.440031
            _cons |   .6418576   .1432754    -1.99   0.047     .4144131    .9941316
------------------------------------------------------------------------------------
```

***ACCESS TO HEALTH SERVICES – ADJUSTED (after checking with Wald test)**

```
( 1)  [KettlePot_D]AdvHealthAccess = 0

           chi2(  1) =    0.26
         Prob > chi2 =    0.6125

Generalized linear models                         No. of obs      =       211
Log pseudolikelihood = -186.3101979               BIC             = -978.5661
                                        (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+------------------------------------------------------------------
BasicHealthAccess |   .9913913   .0134941    -0.64   0.525      .965293    1.018195
 AffordProfCare_D |   1.077164   .1620042     0.49   0.621     .8021617    1.446443
            _cons |   .6086157   .0892847    -3.38   0.001     .4565315    .8113636
------------------------------------------------------------------------------------
```

***ECONOMIC**

"SafeFuel_D" removed because of collinearity with outcome

```
Generalized linear models                         No. of obs      =       200
Log pseudolikelihood = -177.7024066               BIC             = -918.3637
                                       (Std. Err. adjusted for 15 clusters in aa3)
----------------------------------------------------------------------------------
                 |               Robust
     KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
          TVbyHH |   1.197294   .1514687     1.42   0.155     .9343639    1.534213
HomeDurability_D |   1.507307   .3533584     1.75   0.080     .9520379    2.386432
           _cons |   .3545697   .0823795    -4.46   0.000     .2248725     .559071
----------------------------------------------------------------------------------
```

***SOCIO-DEMO**

```
Generalized linear models                         No. of obs      =       206
Log pseudolikelihood = -177.1263894               BIC             = -947.3225
                                   (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------
             |               Robust
 KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 head_hh_age |   .9912999   .0051224    -1.69   0.091     .9813109    1.001391
  HHgender_D |   1.361303   .3764154     1.12   0.265     .7917502    2.340569
   Marital_D |   1.463702   .5269215     1.06   0.290     .7228138    2.964003
  Literacy_D |   1.211879    .207069     1.12   0.261     .8669975    1.693951
HHp_total_in |    1.09171   .0329428     2.91   0.004     1.029015    1.158224
       _cons |   .3083766   .1522371    -2.38   0.017     .1171835    .8115146
------------------------------------------------------------------------------
```

***SOCIO-DEMO – WITH INTERACTION TERMS (no clear need to use)**

```
Generalized linear models                         No. of obs      =       206
Log pseudolikelihood = -177.1261406               BIC             = -941.9951
                                   (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------
             |               Robust
 KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 head_hh_age |   .9913159   .0050775    -1.70   0.089     .9814139    1.001318
  Married__F |    .736438   .2326496    -0.97   0.333     .3964893    1.367858
   Single__M |   .6893089   .2711602    -0.95   0.344     .3188367    1.490251
   Single__F |   .4977071   .3060282    -1.13   0.256     .1491387    1.660953
  Literacy_D |   1.211567   .2098356     1.11   0.268      .862829    1.701257
HHp_total_in |   1.091808   .0318139     3.01   0.003     1.031201    1.155977
       _cons |   .6136567   .1805737    -1.66   0.097     .3447086    1.092443
------------------------------------------------------------------------------
```

***OTHER**

Generalized linear models — No. of obs = 206

Log pseudolikelihood = -179.312637 — BIC = -942.2778

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Q104e	.803252	.1676974	-1.05	0.294	.5335116	1.209372
Q104i	.8666667	.2165662	-0.57	0.567	.5310682	1.41434
Q104u	1.006452	.2768805	0.02	0.981	.586979	1.725692
Q104s	1.453763	.2884582	1.89	0.059	.9853645	2.144819
_cons	.5769231	.1110946	-2.86	0.004	.3955553	.8414506

5.3.2 Hierarchical blocks combined in sequence (with adjustments)

***WATER-RELATED + ACCESS TO HEALTH SERVICES**

Generalized linear models — No. of obs = 195

Log pseudolikelihood = -172.280079 — BIC = -879.3098

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.199978	.2052091	1.07	0.286	.8582394	1.677791
ImprovedSource_D	.9320926	.2272043	-0.29	0.773	.5780595	1.502954
BasicHealthAccess	.9915808	.0128227	-0.65	0.513	.9667645	1.017034
AffordProfCare_D	.9593041	.149326	-0.27	0.790	.7070622	1.301532
_cons	.6286539	.1465306	-1.99	0.046	.3981147	.992693

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC**

Generalized linear models — No. of obs = 182

Log pseudolikelihood = -160.5515043 — BIC = -797.5982

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.216133	.2093875	1.14	0.256	.8678121	1.704263
ImprovedSource_D	.9192585	.228771	-0.34	0.735	.5644217	1.497172
BasicHealthAccess	.991559	.0144023	-0.58	0.559	.9637291	1.020193
AffordProfCare_D	.914861	.131739	-0.62	0.537	.689895	1.213186
TVbyHH	1.162801	.1518793	1.15	0.248	.9001724	1.502052
HomeDurability_D	1.252875	.3672954	0.77	0.442	.7052904	2.225603
_cons	.4802349	.2075173	-1.70	0.090	.2058902	1.120138

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO**

```
Generalized linear models                        No. of obs      =       177
Log pseudolikelihood = -150.5895637              BIC             = -754.8856
                                       (Std. Err. adjusted for 15 clusters in aa3)
```

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.132966	.1868226	0.76	0.449	.8200806	1.565227
ImprovedSource_D	.9802867	.2200542	-0.09	0.929	.6313583	1.522055
BasicHealthAccess	.9963699	.0125094	-0.29	0.772	.9721511	1.021192
AffordProfCare_D	.9357666	.1552819	-0.40	0.689	.675956	1.295438
TVbyHH	1.429947	.1469652	3.48	0.001	1.169058	1.749055
HomeDurability_D	1.071477	.2930972	0.25	0.801	.6268174	1.831575
head_hh_age	.9897304	.0050447	-2.03	0.043	.9798922	.9996673
HHgender_D	1.13956	.2527756	0.59	0.556	.7377766	1.760149
Marital_D	1.423931	.4911924	1.02	0.306	.7242067	2.799725
Literacy_D	1.178157	.2161897	0.89	0.372	.8222604	1.688096
HHp_total_in	1.129661	.0283586	4.86	0.000	1.075424	1.186633
_cons	.2780187	.1631207	-2.18	0.029	.0880344	.8780023

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO + OTHER**

```
Generalized linear models                        No. of obs      =       169
Log pseudolikelihood =  -141.018727              BIC             = -703.0968
                                       (Std. Err. adjusted for 15 clusters in aa3)
```

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.9998877	.1744076	-0.00	0.999	.7103601	1.407421
ImprovedSource_D	1.062646	.2303591	0.28	0.779	.6948106	1.625216
BasicHealthAccess	.9968404	.0123165	-0.26	0.798	.9729905	1.021275
AffordProfCare_D	.8703294	.1539336	-0.79	0.432	.6153654	1.230932
TVbyHH	1.35424	.1934961	2.12	0.034	1.023469	1.791913
HomeDurability_D	1.122308	.3191739	0.41	0.685	.6427446	1.959683
head_hh_age	.9883123	.005101	-2.28	0.023	.9783649	.9983608
HHgender_D	1.082213	.2738188	0.31	0.755	.6590884	1.776976
Marital_D	1.343944	.5086386	0.78	0.435	.640073	2.821844
Literacy_D	1.295753	.259979	1.29	0.197	.8744551	1.920024
HHp_total_in	1.13793	.0271849	5.41	0.000	1.085876	1.192478
Q104e	.8311541	.1573973	-0.98	0.329	.5734398	1.20469
Q104i	.917723	.1724651	-0.46	0.648	.634962	1.326403
Q104u	1.025964	.2483113	0.11	0.916	.6384373	1.648717
Q104s	1.329905	.2964165	1.28	0.201	.859212	2.058454
_cons	.305517	.1982032	-1.83	0.068	.0856685	1.089557

5.3.3 Adjustments & Final Model

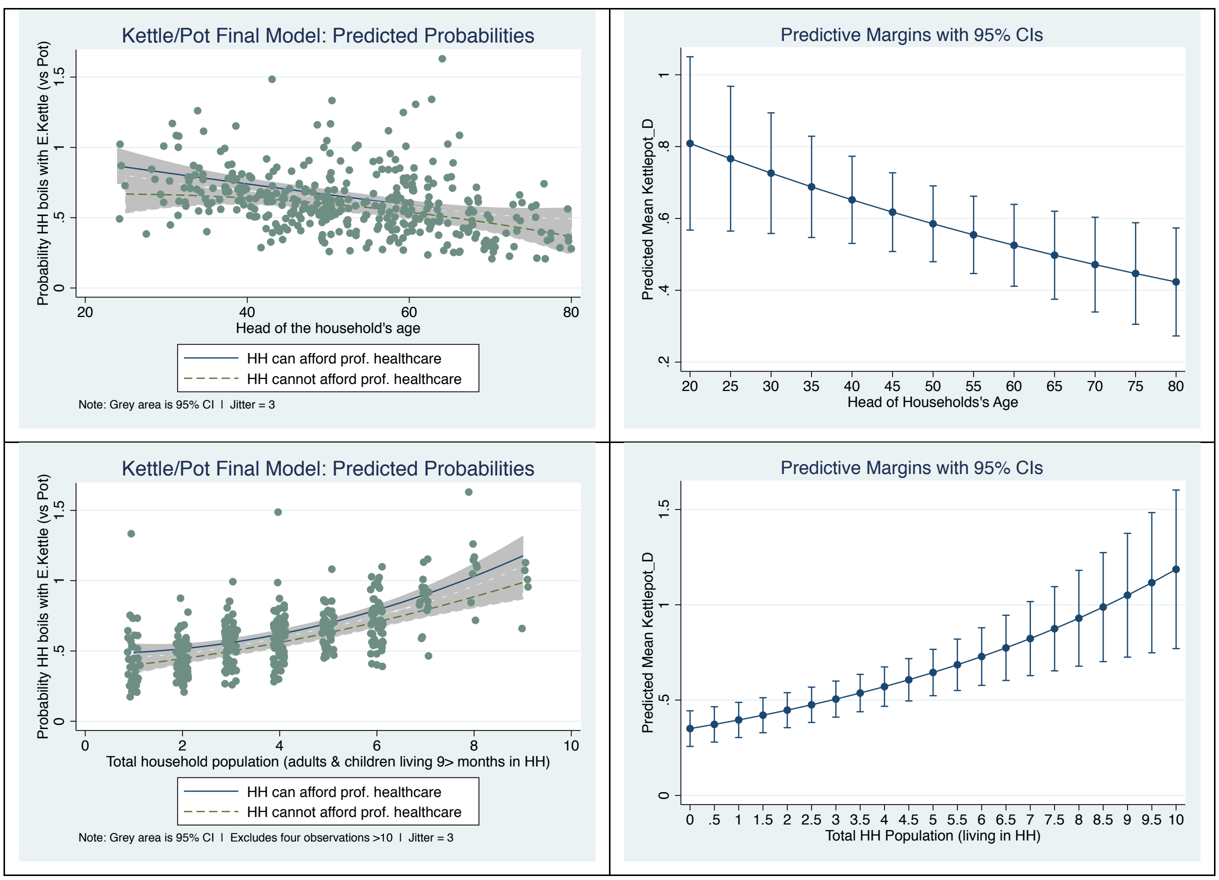
```
Test impact of removing AffordProfCare_D: chi2(  1) =    0.16 (Prob > chi2 =    0.6891)

Generalized linear models                          No. of obs      =       177
Log pseudolikelihood = -150.6274907                BIC             = -759.9859
                                        (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |    1.12343   .1879551     0.70   0.487     .8093497    1.559395
 ImprovedSource_D |   .9923032   .2209143    -0.03   0.972     .6414211    1.535131
BasicHealthAccess |   .9968564   .0119482    -0.26   0.793     .9737113    1.020552
           TVbyHH |   1.423821   .1470664     3.42   0.001     1.162879    1.743315
 HomeDurability_D |   1.035788   .3170914     0.11   0.909      .568444    1.887356
      head_hh_age |    .989262   .0046098    -2.32   0.021      .980268    .9983385
       HHgender_D |   1.138241   .2508116     0.59   0.557     .7390467     1.75306
        Marital_D |   1.427835   .4909016     1.04   0.300     .7278263    2.801097
       Literacy_D |   1.160248   .2017855     0.85   0.393     .8251133    1.631505
     HHp_total_in |   1.129685   .0286036     4.82   0.000     1.074991    1.187161
            _cons |   .2845307   .1607647    -2.22   0.026     .0940125    .8611377
------------------------------------------------------------------------------------
```

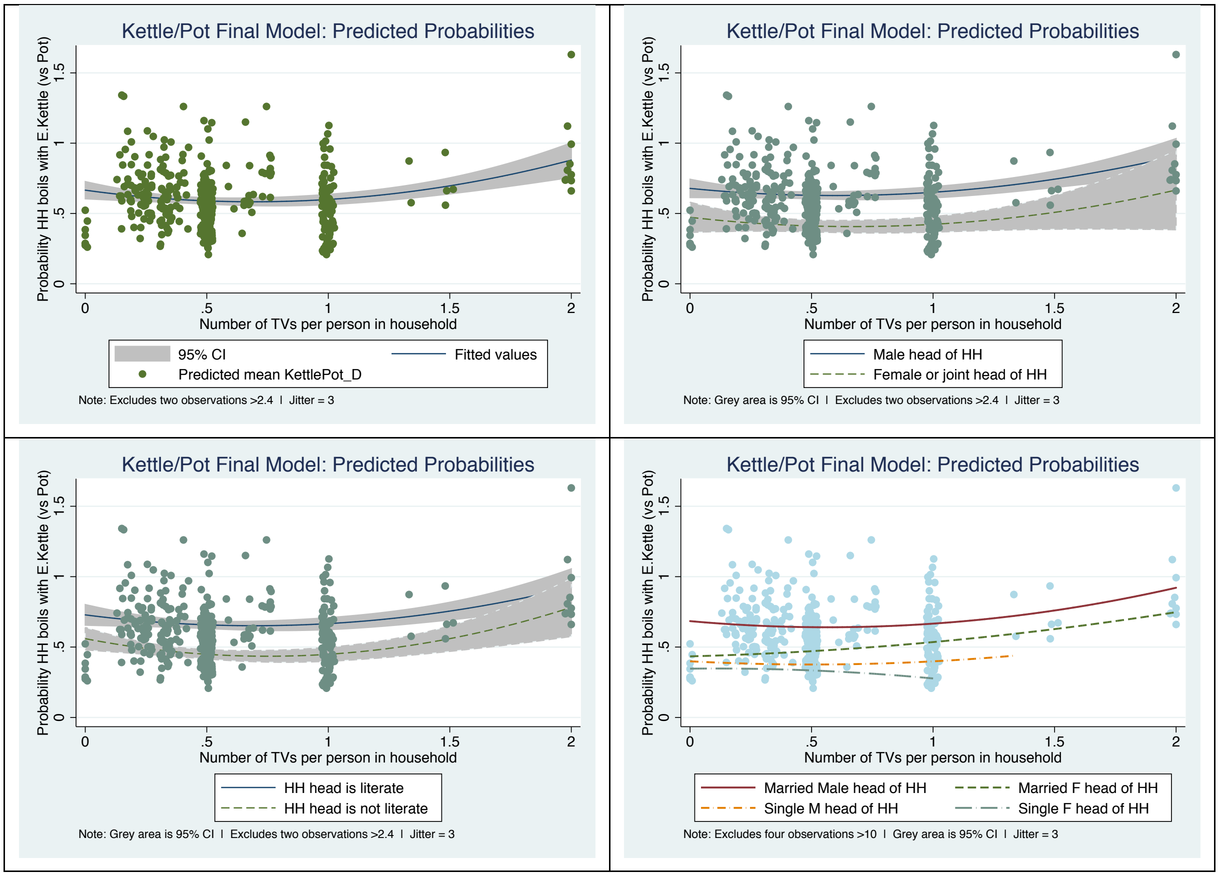
5.3.4 Final Model – Diagnostics & graphs

```
Generalized linear models                          No. of obs      =       177
Optimization     : ML                              Residual df     =       166
                                                   Scale parameter =         1
Deviance         =  99.25498134                    (1/df) Deviance =  .5979216
Pearson          =  74.49842569                    (1/df) Pearson  =  .4487857
Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = ln(u)                    [Log]
                                                   AIC             =  1.826299
Log pseudolikelihood = -150.6274907                BIC             = -759.9859
                                        (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |    1.12343   .1879551     0.70   0.487     .8093497    1.559395
 ImprovedSource_D |   .9923032   .2209143    -0.03   0.972     .6414211    1.535131
BasicHealthAccess |   .9968564   .0119482    -0.26   0.793     .9737113    1.020552
           TVbyHH |   1.423821   .1470664     3.42   0.001     1.162879    1.743315
 HomeDurability_D |   1.035788   .3170914     0.11   0.909      .568444    1.887356
      head_hh_age |    .989262   .0046098    -2.32   0.021      .980268    .9983385
       HHgender_D |   1.138241   .2508116     0.59   0.557     .7390467     1.75306
        Marital_D |   1.427835   .4909016     1.04   0.300     .7278263    2.801097
       Literacy_D |   1.160248   .2017855     0.85   0.393     .8251133    1.631505
     HHp_total_in |   1.129685   .0286036     4.82   0.000     1.074991    1.187161
            _cons |   .2845307   .1607647    -2.22   0.026     .0940125    .8611377
------------------------------------------------------------------------------------
```

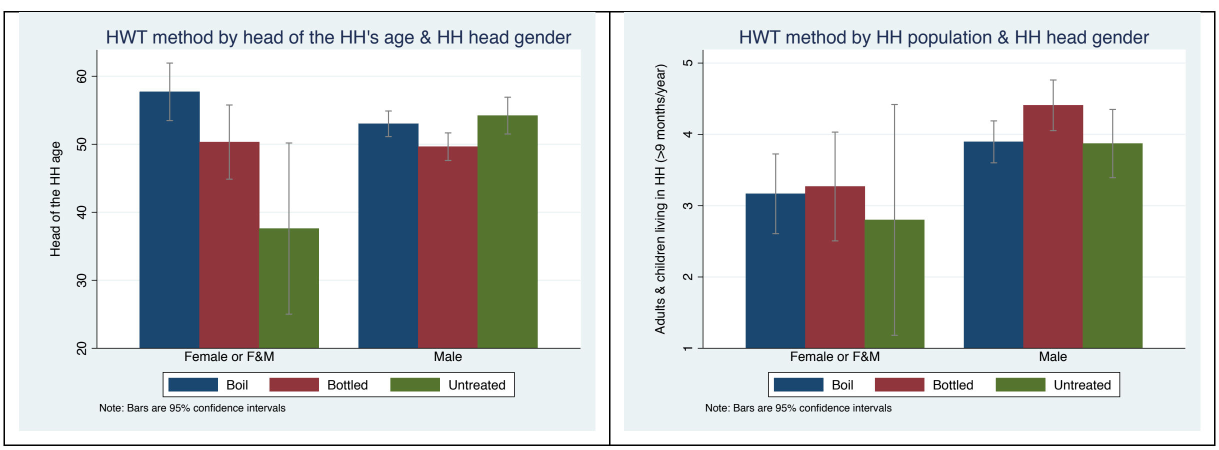
```
                |    esample() from
    E.Kettle=1, |    estimates store
          Pot=0 |         0          1 |     Total
----------------+----------------------+----------
      Boil: Pot |        17         76 |        93
Boil: E. Kettle |        21        101 |       122


Predictive margins                                Number of obs     =        177
Model VCE    : Robust
Expression   : Predicted mean KettlePot_D, predict()
------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .5706215   .0523097    10.91   0.000     .4680963    .6731466
------------------------------------------------------------------------------
```

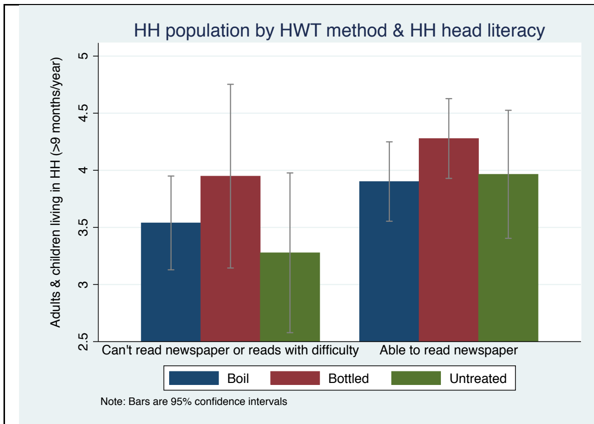
Note: Other graphs provided in chapter three.

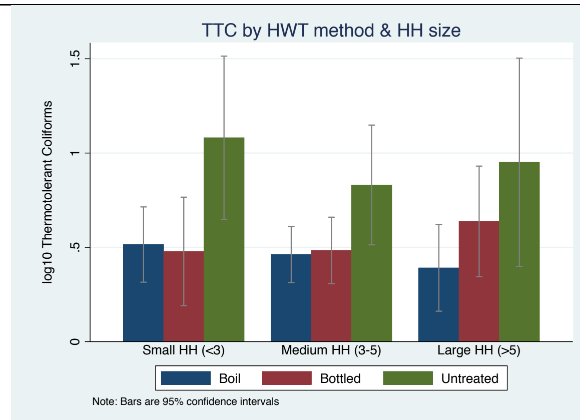




5.3.5 Related analyses








```
                 | Dummy: Male=1, other=0 |
                 |   Exposed   Unexposed  |      Total
-----------------+------------------------+------------
           Cases |       108          14  |        122
        Noncases |        64          28  |         92
-----------------+------------------------+------------
           Total |       172          42  |        214
                 |                        |
            Risk |   .627907    .3333333  |   .5700935
                 |                        |
                 |      Point estimate    |    [95% Conf. Interval]
                 |------------------------+------------------------
 Risk difference |         .2945736       |    .1347509    .4543964
      Risk ratio |         1.883721       |     1.20967    2.933365
 Attr. frac. ex. |         .4691358       |    .1733283    .6590946
 Attr. frac. pop |         .4153005       |
      Odds ratio |            3.375       |    1.668647    6.818201 (Cornfield)
                 +-------------------------------------------------
                               chi2(1) =    11.95  Pr>chi2 = 0.0005
```

5.3.5 Sensitivity analyses

***Bootstrapping (1,000 reps) to see impact on SE estimates**

```
Generalized linear models                         No. of obs      =        177
Log pseudolikelihood = -150.6274907               BIC             = -759.9859
                                         (Replications based on 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |   Observed   Bootstrap                         Normal-based
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |    1.12343    .2196495     0.60   0.552     .7658117     1.64805
  ImprovedSource_D |   .9923032    .2674657    -0.03   0.977     .5850747    1.682974
```

```
BasicHealthAccess |   .9968564    .016893    -0.19   0.853     .9642906    1.030522
           TVbyHH |   1.423821   .1834791     2.74   0.006     1.106028    1.832924
 HomeDurability_D |   1.035788    .363578     0.10   0.920     .5205776    2.060896
      head_hh_age |    .989262   .0049747    -2.15   0.032     .9795597    .9990604
       HHgender_D |   1.138241   .2985455     0.49   0.622     .6807309    1.903238
        Marital_D |   1.427835   2.340527     0.22   0.828     .0574614    35.47967
       Literacy_D |   1.160248   .2212535     0.78   0.436     .7984194    1.686051
      HHp_total_in |   1.129685   .0325444     4.23   0.000     1.067666    1.195306
            _cons |   .2845307    .486715    -0.73   0.462     .0099557    8.131762
------------------------------------------------------------------------------------
```

***Full model**

```
Generalized linear models                          No. of obs      =        109
Log pseudolikelihood = -89.52784858                BIC             = -396.6224
                                  (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
          PercWQ_D |   1.315896   .1473685     2.45   0.014     1.056561    1.638885
  ImprovedSource_D |   .8461037   .1443745    -0.98   0.327     .6055908    1.182137
   RelativesBoil_D |   .9960083   .4259219    -0.01   0.993     .4307889    2.302827
   NeighborsBoil_D |   .8154721   .3472801    -0.48   0.632     .3539265    1.878906
 BasicHealthAccess |    .983405   .0121887    -1.35   0.177     .9598034    1.007587
   AdvHealthAccess |   1.006025   .0038172     1.58   0.113     .9985708    1.013534
  AffordProfCare_D |   .6858321   .2211096    -1.17   0.242     .3645808    1.290155
            TVbyHH |   1.135256   .1294861     1.11   0.266     .9078349    1.419649
  HomeDurability_D |     1.1189   .3313752     0.38   0.704     .6261782     1.99933
        SafeFuel_D |   1.883003   .5859062     2.03   0.042     1.023282    3.465028
       head_hh_age |   .9940319   .0036673    -1.62   0.105       .98687    1.001246
        HHgender_D |   .9861884   .1888268    -0.07   0.942     .6776091    1.435293
         Marital_D |   2.957355   1.463803     2.19   0.028     1.120944    7.802307
        Literacy_D |   1.031738   .1731381     0.19   0.852     .7425527    1.433545
      HHp_total_in |   1.131371   .0492188     2.84   0.005     1.038902     1.23207
             _cons |   .1316543   .1089826    -2.45   0.014     .0259906    .6668901
------------------------------------------------------------------------------------
```

***Full model without RelativesBoil_D NeighborsBoil_D SafeFuel_D**

```
Generalized linear models                          No. of obs      =        176
Log pseudolikelihood = -149.2934235                BIC             =  -744.202
                                  (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                  |               Robust
      KettlePot_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
          PercWQ_D |   1.148129   .1921591     0.83   0.409     .8270418    1.593874
  ImprovedSource_D |   .9681243   .2181508    -0.14   0.886     .6224822    1.505689
 BasicHealthAccess |   .9964654    .011779    -0.30   0.765     .9736444    1.019821
   AdvHealthAccess |   .9997874   .0043872    -0.05   0.961     .9912255    1.008423
```

AffordProfCare_D	.9231075	.1551944	-0.48	0.634	.6639676	1.283387
TVbyHH	1.42107	.1473711	3.39	0.001	1.159691	1.741361
HomeDurability_D	1.069856	.2946388	0.25	0.806	.6235968	1.835467
head_hh_age	.9891765	.0050836	-2.12	0.034	.9792628	.9991906
HHgender_D	1.134769	.2704197	0.53	0.596	.7113164	1.810306
Marital_D	1.409718	.4924536	0.98	0.326	.7108594	2.795635
Literacy_D	1.162356	.2233399	0.78	0.434	.7976013	1.693919
HHp_total_in	1.133928	.0293694	4.85	0.000	1.077802	1.192977
_cons	.291539	.1784421	-2.01	0.044	.087842	.9675891

***No adjustment for clusters, just robust variance estimator for SE (see Cummings 2009)**

```
Generalized linear models                         No. of obs      =        177
Log pseudolikelihood = -150.6274907               BIC             = -759.9859
```

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.12343	.1585983	0.82	0.410	.8518817	1.481539
ImprovedSource_D	.9923032	.1320709	-0.06	0.954	.7644576	1.288058
BasicHealthAccess	.9968564	.0058129	-0.54	0.589	.9855281	1.008315
TVbyHH	1.423821	.1787559	2.81	0.005	1.113242	1.821045
HomeDurability_D	1.035788	.277958	0.13	0.896	.6121351	1.752646
head_hh_age	.989262	.0052321	-2.04	0.041	.9790602	.9995701
HHgender_D	1.138241	.268012	0.55	0.582	.7174788	1.805758
Marital_D	1.427835	.4970067	1.02	0.306	.7217524	2.82467
Literacy_D	1.160248	.1989185	0.87	0.386	.8291191	1.623622
HHp_total_in	1.129685	.0380142	3.62	0.000	1.057582	1.206703
_cons	.2845307	.1509671	-2.37	0.018	.1005764	.8049373

***Adjust for county-clusters only**

```
Generalized linear models                         No. of obs      =        177
Log pseudolikelihood = -150.6274907               BIC             = -811.7474
                                          (Std. Err. adjusted for 2 clusters in aa1)
```

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.12343	.1082773	1.21	0.227	.9300504	1.357019
ImprovedSource_D	.9923032	.2369261	-0.03	0.974	.6214529	1.584457
BasicHealthAccess	.9968564	.0007207	-4.36	0.000	.9954449	.9982699
TVbyHH	1.423821	.251253	2.00	0.045	1.007509	2.012156
HomeDurability_D	1.035788	.0455322	0.80	0.424	.9502826	1.128986
head_hh_age	.989262	.0041627	-2.57	0.010	.9811367	.9974545
HHgender_D	1.138241	.1420454	1.04	0.299	.8912707	1.453647
Marital_D	1.427835	1.02889	0.49	0.621	.3477818	5.862045
Literacy_D	1.160248	.2780476	0.62	0.535	.7253787	1.855825
HHp_total_in	1.129685	.0147523	9.34	0.000	1.101138	1.158972

```
           _cons |   .2845307     .34788    -1.03   0.304     .0259067    3.124974
------------------------------------------------------------------------------------
```

***Compared to mixed effects multilevel logit with OR**

```
Mixed-effects logistic regression               Number of obs      =       177
Group variable:             aa3                 Number of groups   =        15
                                                Obs per group: min =         2
                                                               avg =      11.8
                                                               max =        22
Integration method: mvaghermite                 Integration points =        15
                                                Wald chi2(10)      =     19.71
Log likelihood = -99.850721                     Prob > chi2        =    0.0321
------------------------------------------------------------------------------------
      KettlePot_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |   .8269463   .4101097    -0.38   0.702     .3128518    2.185828
 ImprovedSource_D |   .6912572   .3574499    -0.71   0.475     .2508895     1.90457
BasicHealthAccess |   1.005893   .0170713     0.35   0.729     .9729844    1.039915
           TVbyHH |   3.665056   2.210932     2.15   0.031      1.12356    11.95542
 HomeDurability_D |   .8351028   .6100368    -0.25   0.805     .1995001    3.495721
      head_hh_age |   .9820464   .0149907    -1.19   0.235     .9531003    1.011872
       HHgender_D |   1.215356    .618042     0.38   0.701      .448584    3.292782
        Marital_D |   2.177001   1.483856     1.14   0.254     .5723672    8.280229
       Literacy_D |   1.475758   .6330914     0.91   0.364     .6365822    3.421177
     HHp_total_in |   1.434424   .1633804     3.17   0.002      1.14743    1.793202
            _cons |   .2320754   .3833974    -0.88   0.377     .0091078    5.913522
------------------+-----------------------------------------------------------------
aa3               |
        var(_cons)|   .9894512   .7581256                      .2203925    4.442137
------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =     7.25 Prob>=chibar2 = 0.0035
```

***Compared to single level logit with OR**

```
Logistic regression                               Number of obs   =        177
                                                  LR chi2(10)     =      34.88
                                                  Prob > chi2     =     0.0001
Log likelihood = -103.47623                       Pseudo R2       =     0.1442
------------------------------------------------------------------------------------
      KettlePot_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         PercWQ_D |   1.312684   .5343136     0.67   0.504     .5911367    2.914959
 ImprovedSource_D |   .9183731   .3441568    -0.23   0.820     .4405901    1.914272
BasicHealthAccess |   .9935759   .0134871    -0.47   0.635     .9674902    1.020365
           TVbyHH |   3.164425   1.686256     2.16   0.031     1.113544    8.992541
 HomeDurability_D |   1.073041   .7245095     0.10   0.917     .2856878    4.030337
      head_hh_age |   .9754658   .0136802    -1.77   0.077     .9490183     1.00265
       HHgender_D |   1.276116   .6055984     0.51   0.607     .5034318    3.234742
        Marital_D |   1.890502   1.147879     1.05   0.294     .5750994    6.214575
       Literacy_D |   1.490059   .5797889     1.02   0.305     .6950191    3.194552
```

HHp_total_in	1.465055	.1584114	3.53	0.000	1.185268	1.810888
_cons	.2323271	.3414312	-0.99	0.321	.0130365	4.140357

***Final model without HomeDurability_D**

Generalized linear models No. of obs = 187

Log pseudolikelihood = -159.0610765 BIC = -817.7841

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.136872	.1686417	0.86	0.387	.8500524	1.520468
ImprovedSource_D	.9914954	.2200175	-0.04	0.969	.6418079	1.531709
BasicHealthAccess	.9975508	.0113404	-0.22	0.829	.9755699	1.020027
TVbyHH	1.289323	.1963346	1.67	0.095	.9566282	1.737722
head_hh_age	.9888152	.0051094	-2.18	0.029	.9788515	.9988803
HHgender_D	1.159896	.2463353	0.70	0.485	.7649682	1.758712
Marital_D	1.386045	.4827017	0.94	0.349	.700389	2.742934
Literacy_D	1.160565	.1837245	0.94	0.347	.8509792	1.582777
HHp_total_in	1.117269	.0315494	3.93	0.000	1.057113	1.180848
_cons	.3266392	.1713436	-2.13	0.033	.1168308	.9132279

***Final model with RMBvillageBottle_r19**

Generalized linear models No. of obs = 177

Log pseudolikelihood = -150.5591018 BIC = -754.9465

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.165622	.2294778	0.78	0.436	.7924653	1.71449
ImprovedSource_D	.9689039	.1978601	-0.15	0.877	.6493168	1.445789
BasicHealthAccess	.9965558	.0118114	-0.29	0.771	.9736728	1.019977
TVbyHH	1.44423	.1435724	3.70	0.000	1.18855	1.754911
HomeDurability_D	1.082886	.3771111	0.23	0.819	.5472109	2.142943
head_hh_age	.9894998	.0044253	-2.36	0.018	.9808644	.9982113
HHgender_D	1.157222	.2430628	0.70	0.487	.7667087	1.746638
Marital_D	1.441816	.4906369	1.08	0.282	.7400378	2.809093
Literacy_D	1.172518	.2177599	0.86	0.391	.8147691	1.687348
HHp_total_in	1.12816	.0278126	4.89	0.000	1.074945	1.184011
RMBvillageBottle_r19	1.027711	.0678464	0.41	0.679	.9029782	1.169674
_cons	.2120529	.1984457	-1.66	0.097	.0338738	1.327471

***Final model with reasons don't purchase bottled water**

Generalized linear models No. of obs = 169

Log pseudolikelihood = -141.1587221 BIC = -702.8169

(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
PercWQ_D	.9844154	.1758664	-0.09	0.930	.6936027	1.39716
ImprovedSource_D	1.083043	.2382478	0.36	0.717	.7037173	1.666836
BasicHealthAccess	.9974855	.0119844	-0.21	0.834	.9742709	1.021253
TVbyHH	1.352688	.1927054	2.12	0.034	1.023139	1.788384
HomeDurability_D	1.03384	.3224734	0.11	0.915	.5609814	1.905279
head_hh_age	.9874527	.0047794	-2.61	0.009	.9781295	.9968647
HHgender_D	1.079449	.2728472	0.30	0.762	.6577303	1.771562
Marital_D	1.370656	.5213861	0.83	0.407	.6503371	2.888806
Literacy_D	1.250928	.2393232	1.17	0.242	.8597723	1.820041
HHp_total_in	1.138182	.0282157	5.22	0.000	1.084202	1.194849
Q104e	.8436489	.1674498	-0.86	0.392	.5717588	1.244832
Q104i	.9298744	.1890027	-0.36	0.721	.6243273	1.384957
Q104u	.9881682	.2351802	-0.05	0.960	.6197953	1.575482
Q104s	1.317539	.2825936	1.29	0.199	.8653516	2.006015
_cons	.3197549	.1969969	-1.85	0.064	.0955879	1.069625

***Final model with RelativesBoil_D**

Generalized linear models   No. of obs   =   117
Log pseudolikelihood = -99.45343557   BIC   = -437.1214
(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
PercWQ_D	1.130607	.2220404	0.63	0.532	.7693854	1.66142
ImprovedSource_D	.9748004	.2134663	-0.12	0.907	.6346228	1.497324
BasicHealthAccess	.9883833	.0125684	-0.92	0.358	.9640542	1.013326
TVbyHH	1.194966	.1819225	1.17	0.242	.8866824	1.610435
HomeDurability_D	.8434319	.2464112	-0.58	0.560	.4757392	1.49531
head_hh_age	.9927744	.0051865	-1.39	0.165	.982661	1.002992
HHgender_D	.9972067	.2141571	-0.01	0.990	.6546116	1.519101
Marital_D	2.180268	.7130536	2.38	0.017	1.148486	4.138988
Literacy_D	1.119364	.1622435	0.78	0.437	.8425506	1.487122
HHp_total_in	1.122263	.0391001	3.31	0.001	1.048186	1.201575
RelativesBoil_D	.7514312	.1277169	-1.68	0.093	.5385362	1.048488
_cons	.3451381	.2441251	-1.50	0.133	.0862812	1.380606

***Final model with HHp_total disaggregated into adults and children**

Generalized linear models   No. of obs   =   177
Log pseudolikelihood = -149.4841058   BIC   = -757.0965
(Std. Err. adjusted for 15 clusters in aa3)

KettlePot_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.135179	.1832065	0.79	0.432	.8273497	1.557542
ImprovedSource_D	.9512136	.1847273	-0.26	0.797	.6500897	1.391819
BasicHealthAccess	.9983327	.0119041	-0.14	0.889	.9752715	1.021939
TVbyHH	1.689621	.2039061	4.35	0.000	1.333721	2.140492
HomeDurability_D	1.036163	.303152	0.12	0.903	.5839702	1.838508
head_hh_age	.9857442	.0052656	-2.69	0.007	.9754776	.9961188
HHgender_D	1.112504	.2464205	0.48	0.630	.7207084	1.717289
Marital_D	1.401397	.4727546	1.00	0.317	.7234567	2.714626
Literacy_D	1.133014	.1871495	0.76	0.450	.8196624	1.566157
HHp_a_in	1.250187	.0611085	4.57	0.000	1.135975	1.375882
HHp_c_all	1.008969	.043818	0.21	0.837	.9266408	1.098612
_cons	.2736258	.1526681	-2.32	0.020	.0916713	.8167341

5.4 Bottle/Boil (BtlBoil_D)

5.4.1 Hierarchical blocks in isolation

***WATER-RELATED**

```
Generalized linear models                         No. of obs      =       186
Log pseudolikelihood = -130.8799387               BIC             = -816.1003
                                  (Std. Err. adjusted for 15 clusters in aa3)
```

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.123035	.224697	0.58	0.562	.7587257	1.662271
ImprovedSource_D	.6249843	.2562064	-1.15	0.252	.2798511	1.395761
RelativesBoil_D	.655652	.2352177	-1.18	0.239	.3245649	1.324479
NeighborsBoil_D	1.05319	.3754508	0.15	0.884	.523676	2.118121
_cons	.5219313	.1071656	-3.17	0.002	.3490119	.7805242

***WATER-RELATED – Adjusted**

"RelativesBoil_D" & "NeighborsBoil_D" removed because too much missing data (n=157 & 159)

```
Generalized linear models                         No. of obs      =       348
Log pseudolikelihood = -272.1432628               BIC             = -1772.723
                                  (Std. Err. adjusted for 15 clusters in aa3)
```

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	1.186181	.2294144	0.88	0.377	.8119389	1.732919
ImprovedSource_D	.7057999	.1917456	-1.28	0.200	.4144141	1.202067

```
          _cons |   .4636102   .1049919    -3.39   0.001       .29743    .7226386
--------------------------------------------------------------------------------
```

***WATER-RELATED – Adjusted two**

"ImprovedSource_D" removed because of collinearity (bottled water classified as unimproved)

```
Generalized linear models                          No. of obs      =        351
Log pseudolikelihood = -276.3378365                BIC             = -1792.739
                                   (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------
             |               Robust
   BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    PercWQ_D |   1.287852   .2339076     1.39   0.164     .9021225    1.838512
       _cons |   .3827751    .046981    -7.82   0.000     .3009325    .4868759
------------------------------------------------------------------------------
```

***ACCESS TO HEALTH SERVICES**

```
Generalized linear models                          No. of obs      =        364
Log pseudolikelihood = -279.0418377                BIC             = -1872.892
                                        (Std. Err. adjusted for 15 clusters in aa3)
-----------------------------------------------------------------------------------
                  |               Robust
        BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
BasicHealthAccess |    .981786   .0134581    -1.34   0.180     .9557597    1.008521
  AdvHealthAccess |   .9869061   .0066056    -1.97   0.049      .974044    .9999381
 AffordProfCare_D |   1.065039   .1533342     0.44   0.662     .8031888    1.412256
            _cons |   .6823612   .1017442    -2.56   0.010     .5094423    .9139737
-----------------------------------------------------------------------------------
```

***ACCESS TO HEALTH SERVICES - Adjusted**

```
Generalized linear models                          No. of obs      =        368
Log pseudolikelihood = -283.8519643                BIC             = -1900.746
                                       (Std. Err. adjusted for 15 clusters in aa3)
----------------------------------------------------------------------------------
                 |               Robust
       BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
 AdvHealthAccess |   .9821558   .0071123    -2.49   0.013     .9683143    .9961951
AffordProfCare_D |   1.185416   .1943859     1.04   0.300     .8595874    1.634752
           _cons |   .5984823    .085431    -3.60   0.000      .452424    .7916934
----------------------------------------------------------------------------------
```

***ECONOMIC**

```
Generalized linear models                          No. of obs      =        332
Log pseudolikelihood = -252.5467037                BIC             = -1667.186
                                           (Std. Err. adjusted for 15 clusters in aa3)
--------------------------------------------------------------------------------------
                    |               Robust
```

BtlBoil_D	IRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
TVbyHH	.8091293	.1101327	-1.56	0.120	.6196674	1.056519
RMBvillageBottle_r19	.9850694	.0786585	-0.19	0.851	.8423601	1.151956
HomeDurability_D	.6609158	.1529458	-1.79	0.074	.4199188	1.040224
SafeFuel_D	1.845892	.5549697	2.04	0.041	1.02398	3.327523
_cons	.4633825	.375642	-0.95	0.343	.0946044	2.269697

***ECONOMIC - Adjusted**

"SafeFuel_D" removed because of possible collinearity with outcome

Generalized linear models   No. of obs = 346

Log pseudolikelihood = -270.2955959   BIC = -1750.891

(Std. Err. adjusted for 15 clusters in aa3)

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
TVbyHH	.8433273	.129224	-1.11	0.266	.6245476	1.138746
RMBvillageBottle_r19	.9793213	.0720887	-0.28	0.777	.8477494	1.131313
HomeDurability_D	.6674816	.1367731	-1.97	0.049	.4467045	.9973745
_cons	.768556	.5100358	-0.40	0.692	.2093118	2.822001

***SOCIO-DEMO**

Generalized linear models   No. of obs = 352

Log pseudolikelihood = -267.5407212   BIC = -1785.735

(Std. Err. adjusted for 15 clusters in aa3)

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
head_hh_age	.9872398	.003826	-3.31	0.001	.9797694	.9947672
HHgender_D	.8501458	.2219638	-0.62	0.534	.5096288	1.418185
Marital_D	.861219	.1640628	-0.78	0.433	.5928695	1.251031
Literacy_D	1.598529	.2750042	2.73	0.006	1.140994	2.239534
HHp_total_in	1.06246	.0363333	1.77	0.076	.9935823	1.136113
_cons	.5861313	.1703997	-1.84	0.066	.3315387	1.036229

***SOCIO-DEMO – WITH INTERACTION TERMS (suggests OK to not use interaction terms)**

Generalized linear models   No. of obs = 352

Log pseudolikelihood = -267.4296626   BIC = -1780.093

(Std. Err. adjusted for 15 clusters in aa3)

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
head_hh_age	.9868796	.0039749	-3.28	0.001	.9791196	.994701

```
   Married__F |   1.114002   .3092659     0.39   0.697     .6465139    1.919526
    Single__M |   .9970164   .3791276    -0.01   0.994     .4731758    2.100787
    Single__F |     1.4862   .4208735     1.40   0.162     .8531545    2.588971
   Literacy_D |   1.601371   .2780382     2.71   0.007     1.139468    2.250515
 HHp_total_in |   1.061049   .0366136     1.72   0.086     .9916606    1.135293
        _cons |   .4418437   .1210034    -2.98   0.003     .2583203    .7557511
------------------------------------------------------------------------------
```

5.4.2 Hierarchical blocks combined in sequence (with adjustments)

***WATER-RELATED + ACCESS TO HEALTH SERVICES**

```
Generalized linear models                         No. of obs      =       347
Log pseudolikelihood = -268.4620372               BIC             = -1767.394
                                      (Std. Err. adjusted for 15 clusters in aa3)
----------------------------------------------------------------------------------
                 |               Robust
       BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
         PercWQ_D |   1.159328   .1886813     0.91   0.364     .8426995    1.594924
  AdvHealthAccess |   .9815501   .0066146    -2.76   0.006     .9686709    .9946004
 AffordProfCare_D |    1.12583   .1757458     0.76   0.448     .8290822    1.528792
            _cons |   .5954882   .0902239    -3.42   0.001      .442492    .8013844
----------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC**

```
Generalized linear models                         No. of obs      =       323
Log pseudolikelihood = -246.0977791               BIC             = -1611.543
                                          (Std. Err. adjusted for 15 clusters in aa3)
--------------------------------------------------------------------------------------
                     |               Robust
           BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
            PercWQ_D |   1.030893   .1657585     0.19   0.850     .7522256    1.412796
     AdvHealthAccess |   .9800945   .0056087    -3.51   0.000     .9691631    .9911492
    AffordProfCare_D |   1.570084   .2490236     2.84   0.004     1.150583    2.142535
              TVbyHH |   .8787755   .1544508    -0.74   0.462     .6226922    1.240173
RMBvillageBottle_r19 |   1.062869     .07999     0.81   0.418     .9171058    1.231799
    HomeDurability_D |   .4564473   .1081607    -3.31   0.001      .286872    .7262616
               _cons |   .7058987   .5224237    -0.47   0.638     .1654941    3.010941
--------------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO**

```
Generalized linear models                         No. of obs      =       307
Log pseudolikelihood = -228.4958274               BIC             = -1492.428
                                          (Std. Err. adjusted for 15 clusters in aa3)
--------------------------------------------------------------------------------------
                     |               Robust
           BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
---------------------+----------------------------------------------------------------
            PercWQ_D |   .9859092   .1668385    -0.08   0.933     .7076101    1.373662
     AdvHealthAccess |   .9820362   .0051433    -3.46   0.001     .9720071    .9921688
     AffordProfCare_D |   1.606815   .2447636     3.11   0.002     1.192075    2.165848
              TVbyHH |   .9718759   .1787864    -0.16   0.877     .6776785    1.393792
RMBvillageBottle_r19 |   1.064577   .0871171     0.76   0.444     .9068204    1.249779
    HomeDurability_D |   .4422671   .0907489    -3.98   0.000     .2958191    .6612154
         head_hh_age |   .9875051   .0038232    -3.25   0.001     .9800401    .9950271
          HHgender_D |   1.015952   .2240883     0.07   0.943      .659362     1.56539
           Marital_D |   .9660611   .1989465    -0.17   0.867     .6452259     1.44643
          Literacy_D |   1.207391   .1633778     1.39   0.164     .9261212    1.574084
         HHp_total_in |   1.055483   .0366701     1.55   0.120      .986003    1.129858
               _cons |   .8604214    .700586    -0.18   0.854     .1744345    4.244143
--------------------------------------------------------------------------------------
```

***WATER-RELATED + ACCESS TO HEALTH SERVICES + ECONOMIC + SOCIO-DEMO - ADJUSTED**

```
 ( 1)  [BtlBoil_D]TVbyHH = 0

           chi2(  1) =    0.02
         Prob > chi2 =    0.8768

Generalized linear models                          No. of obs      =        312
Log pseudolikelihood = -233.4583727                BIC             = -1527.727
                                          (Std. Err. adjusted for 15 clusters in aa3)
--------------------------------------------------------------------------------------
                     |               Robust
           BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
            PercWQ_D |   .9972099   .1612773    -0.02   0.986     .7263117    1.369147
     AdvHealthAccess |   .9828467   .0051586    -3.30   0.001     .9727879    .9930094
    AffordProfCare_D |   1.588992   .2520869     2.92   0.004     1.164346    2.168509
RMBvillageBottle_r19 |   1.065928   .0822156     0.83   0.408     .9163772    1.239885
    HomeDurability_D |   .4554386   .1017278    -3.52   0.000     .2939704    .7055961
         head_hh_age |   .9870974   .0033668    -3.81   0.000     .9805206    .9937184
          HHgender_D |   1.049374   .2435347     0.21   0.835      .665866    1.653766
           Marital_D |   .9108475   .1938692    -0.44   0.661     .6001666    1.382355
          Literacy_D |    1.20598   .1555542     1.45   0.146     .9365851    1.552862
        HHp_total_in |   1.053208   .0323959     1.69   0.092     .9915888    1.118655
               _cons |   .8583043   .6384408    -0.21   0.837     .1997486    3.688067
--------------------------------------------------------------------------------------
```

5.4.3 Final Model

FINAL ADJUSTMENT

```
 ( 1)  [BtlBoil_D]PercWQ_D = 0

           chi2(  1) =    0.00
         Prob > chi2 =    0.9862
```

```
Generalized linear models                          No. of obs      =       331
Optimization     : ML                              Residual df     =       321
                                                   Scale parameter =         1
Deviance         =  214.0843027                    (1/df) Deviance =  .6669293
Pearson          =  189.2114889                    (1/df) Pearson  =  .5894439
Variance function: V(u) = u                        [Poisson]
Link function    : g(u) = ln(u)                    [Log]
                                                   AIC             =  1.547082
Log pseudolikelihood = -246.0421513                BIC             = -1648.396
                                          (Std. Err. adjusted for 15 clusters in aa3)
```

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AdvHealthAccess	.9833141	.0056761	-2.92	0.004	.9722518	.9945022
AffordProfCare_D	1.610418	.2539458	3.02	0.003	1.18226	2.193633
RMBvillageBottle_r19	1.066082	.0868199	0.79	0.432	.9088036	1.250578
HomeDurability_D	.4864722	.0801281	-4.37	0.000	.3522528	.6718335
head_hh_age	.9854231	.0036583	-3.96	0.000	.978279	.9926194
HHgender_D	.9953426	.2184256	-0.02	0.983	.6474085	1.530265
Marital_D	.9315593	.1896292	-0.35	0.728	.625085	1.388296
Literacy_D	1.259746	.1468175	1.98	0.048	1.002489	1.583021
HHp_total_in	1.052844	.035242	1.54	0.124	.9859884	1.124233
_cons	.8454913	.6156729	-0.23	0.818	.2028982	3.523223

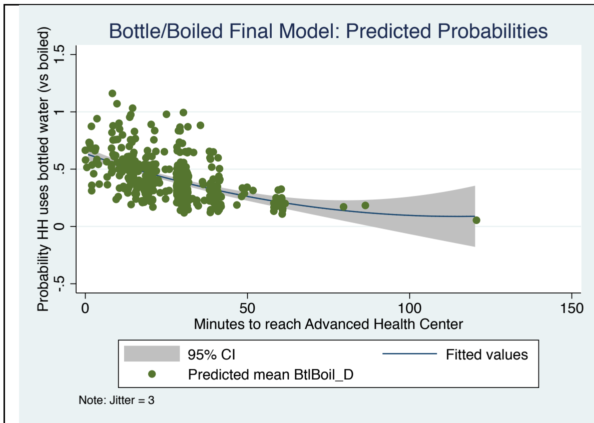
5.4.4 Final Model – Diagnostics & graphs

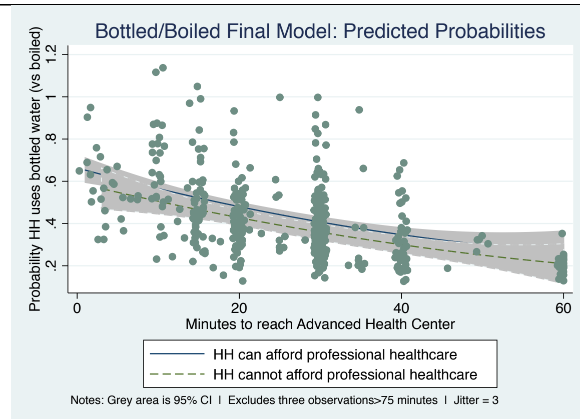
Bottled=1, Boil=0	esample() from estimates store 0	1	Total
Boil	23	192	215
Bottle	18	139	157

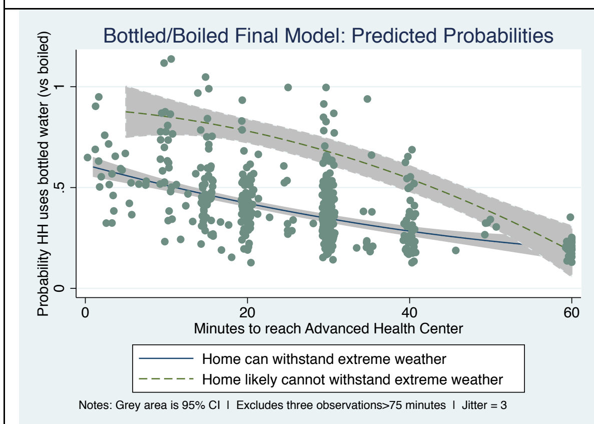
```
Predictive margins                                Number of obs   =       331
Model VCE    : Robust
Expression   : Predicted mean BtlBoil_D, predict()
```

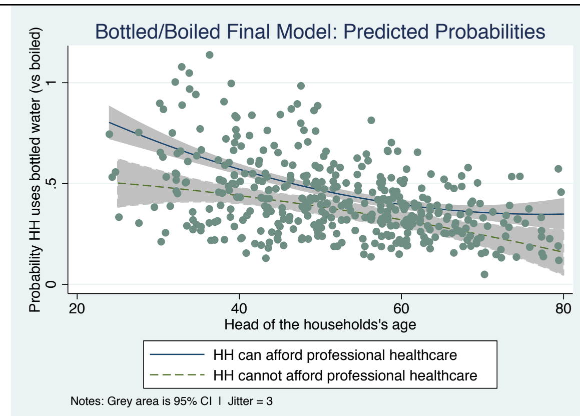
	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.4199396	.0538113	7.80	0.000	.3144713	.5254079

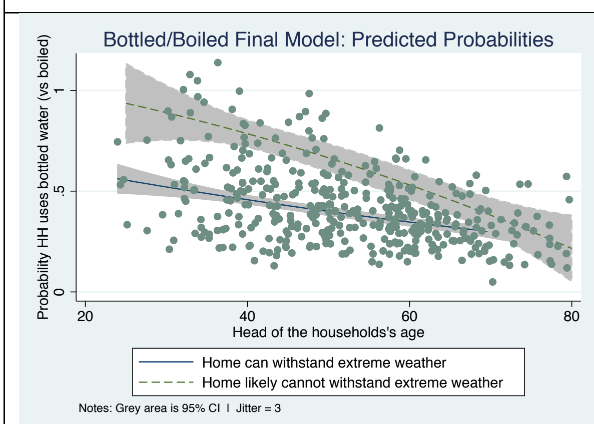
Note: Other graphs provided in chapter four.











Dummy: Home is durable=1	Cat: Boil, Bottled, or Untreated Boil	Bottled	Untreated	Total
Home cannot withstand	9.85	18.12	11.11	12.97
Home can withstand ex	90.15	81.88	88.89	87.03

COUNTY A

durable=1	Boil	Bottled	Untreated	Total
Home cannot withstand	16.39	32.53	31.58	23.66
Home can withstand ex	83.61	67.47	68.42	76.34

COUNTY B

durable=1	Boil	Bottled	Untreated	Total
Home cannot withstand	0.00	0.00	3.77	1.00
Home can withstand ex	100.00	100.00	96.23	99.00

5.4.5 Sensitivity analyses

. *Bootstrapping (1,000 reps) to see impact on SE estimates

Generalized linear models No. of obs = 331

Log pseudolikelihood = -246.0421513 BIC = -1648.396

(Replications based on 15 clusters in aa3)

BtlBoil_D	Observed IRR	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
AdvHealthAccess	.9833141	.006164	-2.68	0.007	.9713068	.9954698
AffordProfCare_D	1.610418	.2872428	2.67	0.008	1.135308	2.284354
RMBvillageBottle_r19	1.066082	.1091956	0.62	0.532	.8721766	1.303096
HomeDurability_D	.4864722	.0942631	-3.72	0.000	.3327529	.7112041
head_hh_age	.9854231	.0039433	-3.67	0.000	.9777247	.9931822
HHgender_D	.9953426	.2332665	-0.02	0.984	.6287626	1.575645
Marital_D	.9315593	.2045113	-0.32	0.747	.605816	1.432453
Literacy_D	1.259746	.1675857	1.74	0.083	.9706141	1.635006
HHp_total_in	1.052844	.0368058	1.47	0.141	.983122	1.127511
_cons	.8454913	.7692682	-0.18	0.854	.1421169	5.030055

***Full model (without RelativesBoil_D NeighborsBoil_D SafeFuel_D)**

Generalized linear models No. of obs = 305

Log pseudolikelihood = -223.0271866 BIC = -1476.556

(Std. Err. adjusted for 15 clusters in aa3)

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
PercWQ_D	.8840969	.1459255	-0.75	0.455	.6397407	1.221788
ImprovedSource_D	.6716547	.1961673	-1.36	0.173	.3789128	1.190564
BasicHealthAccess	.9814092	.0097412	-1.89	0.059	.9625013	1.000689
AdvHealthAccess	.9870086	.0054681	-2.36	0.018	.9763492	.9977843
AffordProfCare_D	1.420562	.2341596	2.13	0.033	1.028375	1.962315
TVbyHH	.9604104	.1502533	-0.26	0.796	.7067877	1.305043

RMBvillageBottle_r19	1.069971	.0692119	1.05	0.296	.9425656	1.214599
HomeDurability_D	.4222091	.0778945	-4.67	0.000	.2940946	.6061333
head_hh_age	.9859824	.0034407	-4.05	0.000	.9792618	.9927491
HHgender_D	.9811567	.1937647	-0.10	0.923	.6662511	1.444903
Marital_D	.900926	.1794312	-0.52	0.600	.6097632	1.33112
Literacy_D	1.166423	.1511486	1.19	0.235	.9048048	1.503687
HHp_total_in	1.044734	.0342337	1.34	0.182	.9797462	1.114032
_cons	1.559316	1.014236	0.68	0.495	.4357943	5.579389

***No adjustment for clusters, just robust variance estimator for SE (see Cummings 2009)**

Generalized linear models   No. of obs   =   331

Log pseudolikelihood = -246.0421513   BIC   = -1648.396

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AdvHealthAccess	.9833141	.004692	-3.53	0.000	.9741607	.9925534
AffordProfCare_D	1.610418	.2886502	2.66	0.008	1.133365	2.288271
RMBvillageBottle_r19	1.066082	.0466228	1.46	0.143	.9785094	1.161491
HomeDurability_D	.4864722	.0948728	-3.69	0.000	.3319365	.7129532
head_hh_age	.9854231	.0051944	-2.79	0.005	.9752948	.9956567
HHgender_D	.9953426	.1885852	-0.02	0.980	.6865899	1.442938
Marital_D	.9315593	.1991917	-0.33	0.740	.6126344	1.41651
Literacy_D	1.259746	.2095354	1.39	0.165	.9092879	1.745278
HHp_total_in	1.052844	.0342545	1.58	0.113	.9878025	1.122169
_cons	.8454913	.4715614	-0.30	0.763	.283376	2.52264

***Adjust for county-clusters only**

Generalized linear models   No. of obs   =   331

Log pseudolikelihood = -246.0421513   BIC   = -1700.615

(Std. Err. adjusted for 2 clusters in aa1)

BtlBoil_D	IRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AdvHealthAccess	.9833141	.0055083	-3.00	0.003	.9725771	.9941696
AffordProfCare_D	1.610418	.0603443	12.72	0.000	1.496384	1.733142
RMBvillageBottle_r19	1.066082	.0031876	21.40	0.000	1.059852	1.072348
HomeDurability_D	.4864722	.0088566	-39.58	0.000	.4694197	.5041442
head_hh_age	.9854231	.0011244	-12.87	0.000	.9832219	.9876293
HHgender_D	.9953426	.2404829	-0.02	0.985	.619891	1.598195
Marital_D	.9315593	.1419356	-0.47	0.642	.6910644	1.255748
Literacy_D	1.259746	.145157	2.00	0.045	1.005082	1.578936
HHp_total_in	1.052844	.0300527	1.80	0.071	.9955594	1.113425
_cons	.8454913	.3423487	-0.41	0.679	.3823388	1.869692

***Compared to mixed effects multilevel logit with OR**

```
Mixed-effects logistic regression               Number of obs      =       331
Group variable:             aa3                 Number of groups   =        15
                                                Obs per group: min =        14
                                                               avg =      22.1
                                                               max =        30
Integration method: mvaghermite                 Integration points =        15
                                                Wald chi2(9)       =     39.32
Log likelihood = -181.32576                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------------
           BtlBoil_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
     AdvHealthAccess |   .9763081   .0119185    -1.96   0.050     .9532254    .9999496
    AffordProfCare_D |   2.550489   .9022659     2.65   0.008     1.274973    5.102067
RMBvillageBottle_r19 |   1.212074   .2731742     0.85   0.393      .779269    1.885258
    HomeDurability_D |   .1552062   .0731829    -3.95   0.000     .0615957    .3910821
         head_hh_age |   .9636079   .0113804    -3.14   0.002     .9415589    .9861732
          HHgender_D |   .8776643   .3702629    -0.31   0.757     .3839101    2.006446
           Marital_D |   .9636546   .4910819    -0.07   0.942     .3549327    2.616356
          Literacy_D |   2.034645   .6773343     2.13   0.033     1.059555    3.907096
         HHp_total_in |    1.13254   .0810842     1.74   0.082     .9842642    1.303153
               _cons |   2.176357   4.536336     0.37   0.709     .0366024    129.4049
---------------------+--------------------------------------------------------------
aa3                  |
           var(_cons)|   1.902762   1.038488                      .6528546    5.545651
------------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =    38.38 Prob>=chibar2 = 0.0000
```

***Compared to single level logit with OR**

```
Logistic regression                               Number of obs   =        331
                                                  LR chi2(9)      =      49.31
                                                  Prob > chi2     =     0.0000
Log likelihood = -200.51345                       Pseudo R2       =     0.1095
------------------------------------------------------------------------------------
           BtlBoil_D | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
     AdvHealthAccess |   .9687775   .0094683    -3.25   0.001     .9503965    .9875139
    AffordProfCare_D |   2.296474   .7116586     2.68   0.007     1.251069    4.215431
RMBvillageBottle_r19 |   1.134504   .0918084     1.56   0.119     .9681077    1.329501
    HomeDurability_D |   .2200024   .0914565    -3.64   0.000     .0974041    .4969099
         head_hh_age |   .9709407   .0100078    -2.86   0.004     .9515226    .9907551
          HHgender_D |   1.011935   .3816682     0.03   0.975     .4831785    2.119324
           Marital_D |   .8940767   .3922774    -0.26   0.799     .3783632    2.112714
          Literacy_D |   1.532679   .4541382     1.44   0.150     .8575057    2.739462
         HHp_total_in |   1.103148   .0676919     1.60   0.110     .9781419     1.24413
               _cons |   3.728109   4.220926     1.16   0.245     .4052912    34.29336
------------------------------------------------------------------------------------
```

***Final model with HHp_total disaggregated into adults and children**

```
Generalized linear models                         No. of obs      =       331
Log pseudolikelihood = -245.7900583               BIC             = -1643.098
                                           (Std. Err. adjusted for 15 clusters in aa3)
------------------------------------------------------------------------------------
                     |               Robust
           BtlBoil_D |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
     AdvHealthAccess |   .9833216   .0056956    -2.90   0.004     .9722216    .9945483
    AffordProfCare_D |   1.605213   .2473627     3.07   0.002     1.186759    2.171213
RMBvillageBottle_r19 |   1.061861   .0901384     0.71   0.480     .8991071    1.254075
    HomeDurability_D |   .4774083   .0787541    -4.48   0.000     .3455208     .659638
         head_hh_age |   .9842672   .0041054    -3.80   0.000     .9762536    .9923465
          HHgender_D |   .9921366   .2178011    -0.04   0.971     .6452224    1.525575
           Marital_D |   .9311975   .1934294    -0.34   0.731     .6197681    1.399118
          Literacy_D |   1.247015   .1516594     1.82   0.070     .9825398     1.58268
            HHp_a_in |   1.086706   .0448884     2.01   0.044     1.002194    1.178345
           HHp_c_all |   1.002916   .0717696     0.04   0.968     .8716698    1.153925
               _cons |   .9141438   .7036391    -0.12   0.907     .2022198    4.132429
------------------------------------------------------------------------------------
```