Environment for Development

Discussion Paper Series May 2015 ■ EfD DP 15-08

A Simple Stated Preference Tool for Estimating the Value of Travel Time in Rural Africa

Joseph Cook, Peter Kimuyu, Annalise G. Blum, and Josephine Gatua

Environment for Development

RESOURCES FOR THE FUTURE

Environment for Development Centers

Central America
Research Program in Economics and Environment for Development in Central America
Tropical Agricultural Research and Higher Education Center (CATIE)
Email: centralamerica@efdinitiative.org

Chile
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción
Email: chile@efdinitiative.org

China
Environmental Economics Program in China (EEPC)
Peking University
Email: china@efdinitiative.org

Ethiopia
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: ethiopia@efdinitiative.org

Kenya
Environment for Development Kenya
University of Nairobi with
Kenya Institute for Public Policy Research and Analysis (KIPPRA)
Email: kenya@efdinitiative.org

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

Tanzania
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

Sweden
Environmental Economics Unit
University of Gothenburg
Email: info@efdinitiative.org

USA (Washington, DC)
Resources for the Future (RFF)
Email: usa@efdintiative.org

The Environment for Development (EfD) initiative is an environmental economics program focused on international research collaboration, policy advice, and academic training. Financial support is provided by the Swedish International Development Cooperation Agency (Sida). Learn more at www.efdinitiative.org or contact info@efdinitiative.org.

Contents

A simple stated preference tool for estimating the value of travel time in rural Africa

Joseph Cook*[1], Peter Kimuyu[2], Annalise G. Blum[3], and Josephine Gatua[4]

[1]*Daniel J. Evans School of Public Affairs, University of Washington*
[2]*School of Economics, University of Nairobi*
[3]*Dept. of Civil and Environmental Engineering, Tufts University*
[4]*Dept. of Economics, University of Gothenburg*

May 2015

Abstract

Despite its importance in benefit-cost analyses in the water supply, transportation, and health care sectors, there are relatively few empirical estimates of the value of travel time savings (VTT) in low-income countries, particularly in rural areas. Analysts instead often rely on a textbook "rule of thumb" of valuing time at 50% of prevailing unskilled wage rates, though these benchmarks have little empirical support in these settings. We estimate the value of travel time through the use of a repeated discrete choice stated preference exercise. We asked 325 rural households in Meru County, Kenya to rank two new hypothetical water sources against their current water source. The two new hypothetical sources were described as safe and reliable to use, but varied only in their distance from the household and the price charged per water container. Results from random-parameters logit models imply an average value of travel time of 18 Ksh/hr, and generally support the 50% rule. These models produce the first individual-level VTT estimates reported in a low-income setting, and indicate statistically-significant heterogeneity in VTTs, though the heterogeneity is not well correlated with observables. A latent class approach identifies four classes of respondents: one class (about one-third of respondents) values time very highly (49 Ksh/hr), one poorer group values time hardly at all (less than 1 Ksh/hr), and two groups value time at approximately 9 Ksh/hr.

Keywords: Value of travel time; Water supply; Africa; Discrete choice experiment

*Corresponding author: email: *jhcook@uw.edu*. We thank Mark Mwiti and John Wainana for excellent assistance with fieldwork, data entry and data analysis. We also thank Dale Whittington, Greg Characklis, and seminar participants at the University of Colorado-Denver School of Public Affairs and the 8th Annual Meeting of the Environment for Development Initiative for helpful comments. We gratefully acknowledge funding support from Environment for Development - Kenya.

A simple stated preference tool for estimating the value of travel time in rural Africa

1 Introduction

The value of travel time savings (VTT) plays a central role in many benefit-cost analyses. The rich literature examining how people trade money and time spent travelling or waiting has focused mainly around route, mode and speed choices in transportation analysis, or around site choices in analysis of recreational demand for enviromental or cultural amenties. Because there are a number of existing studies, benefit-cost analysts usually find that the costs of primary data collection for site-specific VTT estimates outweigh the benefits and instead rely on benefit transfer approaches. In particular, there has developed a consensus towards using several benchmark values expressed as percentages of after-tax wages. For example, one popular textbook (Boardman et al., 2010, Table 16-5, p.419), citing meta-analyses by Waters (1996) and Von Wartburg and Waters (2004), recommends using 50% of the after-tax wage rate as the central VTT estimate for commuting or leisure time, 100% of the wage rate for walking or driving in congestion, and 125% of the wage rate for waiting.

Nearly all of these studies, however, have been conducted in industrialized countries. Time savings are an important component of many investment analyses in developing countries, in particular around transportation, labor-saving technologies, access to energy and firewood collection, and water infrastructure access. Analysts in developing countries could choose to transfer these rules of thumb to local wage rates, but the empirical evidence is thin that the rule transfers well from wealthy auto and train commuters to poor rural villagers walking to water, or to slum residents walking along busy highways into the central city. There are in fact relatively few empirical estimates of the value of travel or waiting time in low-income countries – as we discuss in the next section – and estimates vary considerably. Furthermore, reliable secondary data on wage rates and the distribution of income can be difficult to obtain at the local level in low-income countries. Because respondents may not truthfully reveal their true income in surveys, researchers are more likely to rely on constructed wealth indices of observable assets (as we do in this paper). In response, the value of travel time is often reported as a fraction of unskilled wages in "casual" or agricultural labor.

In this paper we report the results from a simple stated preference experiment around people's willingness to trade time and money in collecting water in rural Kenya. We offered 325 households the hypothetical choice between their current primary water source and two new hypothetical water sources that we asked them to assume were safe and reliable. The new sources differed only in the amount of time needed to collect water and the price charged. The paper's contribution is two-fold. First, we add to the few existing empirical estimates of the value of time in low-income countries. We do, in fact, find support for the benchmark of 50% of unskilled wages. By exploiting the panel nature of the stated preference exercise, the paper is the first (to our knowledge) to report individual-level estimates of the value of travel time savings in a low-income country. We use both random-parameters logit and latent class multinomial logit frameworks. We find that models that incorporate heterogeneity in preferences for time and price fit the data better, but that individual-level VTTs are not well correlated with observable characteristics like wealth indices or income.

Second, our approach is simple and could be easily replicated in other areas of low-income countries to build a better knowledge base around valuing travel time savings in low-income countries. It could be applied in any situation - still unfortunately common across the globe – where people are either bringing water back to the home or paying a "water vendor" to bring it to them. It might also be adapted to the decision to collect or purchase firewood.

The paper has further policy relevance in that it explores the preferences of some of the 748 million people globally without access to "improved" drinking water, over 90% of whom live in rural areas (World Health Organization and UNICEF, 2014). In Kenya, the location of our study, only 54% of rural people have access to improved sources of drinking water, compared to 83% of urban dwellers. To extend and *maintain* water supply to rural populations, it is important to understand the relative importance of a water source's cost, quality, distance from home, availability during the day, and its potential for causing conflict with neighbors when used. Given the expense of installing water infrastructure, a particularly important question is how close water points must be for to households to use them, and how households trade off proximity with user fees or tariffs that are needed to both expand rural water infrastructure and properly maintain existing facilities.

We proceed by first outlining the existing estimates of VTT in low-income countries, and then describe our study site in rural Kenya and households' existing water supply situation there. Section 4 describes the hypothetical scenario given to respondents and discusses the likelihood that respondents understood it and answered it seriously and carefully. We briefly and verbally sketch our econometric approach in Section 4.1, leaving the details to Appendix A1.4 for interested readers. We then report our VTT results and robustness to a number of different assumptions, and conclude with a summary of the key results and thoughts on replicating the study elsewhere.

2 Existing estimates of the value of travel time in low-income countries

In the transportation sector, two studies in low-income countries have estimated VTTs by examining actual mode choices in a nested logit framework. Dissanayake and Morikawa (2002) report a mean VTT of 27 baht/hr in Bangkok in 1995 (they do not report results as a fraction of wages or income), and Walker et al. (2010) find the implied VTT ranges from 51- 86% of city-wide average income in (urban) Chengdu, China. Liu (2007) adds a stated preference component to revealed mode choices, asking 100 households in Shanghai to rank-order their transportation choices. VTT estimates averaged 64% of in-sample wage rates for in-vehicle time and 82% of wages for out-of-vehicle time. Alpizar and Carlsson (2003) use a repeated discrete choice approach similar to ours, asking car commuters in San Jose, Costa Rica to make several hypothetical choices between continuing to commute by car or switching to a public bus. The authors also model data using a random-parameters logit framework, and find mean values of VTT of 40-50% of the sample's hourly wages, with higher willingness-to-pay for reductions in travel times by bus than by car. Jeuland et al. (2010) applied the travel cost method to households' decisions to travel and wait to receive free cholera vaccines in Beira, Mozambique. Value of travel times, inferred from count models based on the pecuniary cost of travel (bus fares, etc) implied that respondents valued travel time at 18-46% of the median hourly wage (Jeuland et al., 2010, Table 2, p.317). With the exception of Jeuland et al. (2010), these studies all survey relatively wealthy residents of urban areas, and none of these studies explored individual-level VTT estimates.

In the water sector, Whittington et al. (1990) used two methods to value travel time in a small Kenyan town, both of which relied on actual water source decisions. The first bounded VTTs by exploiting differences in collection times (including walking, waiting and filling containers) and prevailing prices paid between free open wells, water kiosks and water vendors who would deliver water to the house, along with times needed to collect from each of these. The second used a multinomial logit discrete choice framework. Applied to data from 69 households, both approaches found that the value of travel time was approximately 100% of unskilled wages. Asthana (1997) also analyzed 490 households' water source decisions in rural India using a discrete choice model and found the VTT was approximately 35% of the unskilled wage rate. Kremer et al. (2011) examined decisions to travel to springs that had been randomly-selected for protection from contamination in rural Kenya. Choices, as well as stated rankings of sources, were modeled with a random parameters logit framework with a focus on exploring how households valued improvements in quality and expected reductions in child diarrhea and child deaths against minutes spent walking to a protected source. To value time, however, the authors used results from a double-bounded, dichotomous choice contingent valuation task. The first version of the task asked households how much they would be willing to pay to "keep their spring" protected. The second version asked households how many minutes they would be willing to walk to access a protected spring. For the 104 respondents with responses to both questions, they divide the willingness to walk by the willingness to pay to derive the VTT, which they estimate has a mean of $0.088 per 8-hr day, or only 7% of unskilled or casual labor wage rates. Our approach differs from Kremer et al. (2011) in several ways. First, our valuation task explicitly presents respondents with the tradeoff between time and money, rather than relying on the ratio of two separate valuation exercises. This also allows us to model responses in a richer random-parameters logit framework and report individual-level VTT estimates.[1] Finally, the average self-reported one-way walking time in their site was 9 minutes. These are much lower than distances in our site, as we describe below, which may imply that travel time to water is more salient to households in our setting.

3 Study Site and Sample

We interviewed a total of 387 households near the small market town of Kianjai in September 2013, the dry season. Kianjai is approximately 20 miles from the city of Meru, in north-central Kenya. The study site was chosen purposefully because of the large number of existing water source options available; the choice experiment reported here was part of a larger study on rural water source choices. Households were, however, chosen randomly based on a transect approach. More details on the study region and sampling approach are provided in Appendix A1.1.

A team of seven trained enumerators asked households a number of detailed questions in Meru (the local language) about the water sources that households could use and do use, during both the dry season and the rainy season. The survey asked about distances to all sources, prices charged, trips taken, perceptions of health risk from drinking water, and the likelihood of conflict in using that source. Of these sources, we asked which they used "overall, for most purposes", which we refer to below as their "primary source". The survey also asked about household demographics and socioeconomic status (income, assets, land ownership, etc.). We interviewed the household member "who is mostly responsible for water-related decisions such as where to get water and how much to collect"; this person was also the person "who collected

[1] Kremer et al. (2011) observed only bounded values of time and money and assigned individual values based on the median of a normal distribution fit to the data (see footnote 18, pg. 185 of their paper). Only the summary statistics of the distribution of VTT are reported, and the underlying individual-level estimates are not reported or explored. To produce VTT estimates for the remainder of their sample, the paper mentions (pg. 185) a regression of these VTT estimates on education, number of children and asset ownership, but the results from this regression are not discussed or presented in the paper or either of the two supplementary appendices.

the most water in the past seven days" in three-quarters of the cases. Eighty percent of respondents were women.

We interviewed 58 households that had private piped connections inside their compounds and two households that had invested in extensive rainwater collection systems, but drop them from the remainder of the paper because they would have had little reason to take our hypothetical choice of two new water points away from the home seriously. An additional group of 78 households said their primary water source was a private well on their compound. Because these water sources are very close, the households have solved their "quantity" problem, but because the shallow, hand-dug wells are typically unprotected, they are unsafe. Seventy percent of these respondents told us that drinking water from their well posed "some" or "serious" health risk (see Table 2) , so the households' water "quality" problem remains. Because respondents are told that our new hypothetical sources would be completely safe to drink, it is plausible that some households with private wells might choose the new, hypothetical source even though it is farther away and has a volumetric price. In some model specifications reported below, we include these respondents, but we begin by focusing on the 247 households that reported either walking to collect water as their primary source (n=237) or paying a "water vendor" to bring water to their home (n=15) on a bicycle or cart.

A typical sample household is Catholic and has five members. The household is led by a married couple, both of whom are around forty years old and have each completed seven years of education. They own their house and two acres of land. The household has a private pit latrine, but does not have electricity. Kerosene is used for lighting and firewood is used for cooking and heating. There are two rooms in the main house and three other buildings in the compound. Monthly household income from all sources is approximately 35,000 Ksh or 407 USD. The most common source of income by far is farming. Thirty-nine percent of households, however, had at least one household member who earned income from full-time employment, part-time or seasonal employment, or business and self-employment; roughly 10% of households had more than one member earning income from these sources. We did not ask about wage rates for each household member separately but rather reported household income, by source, for all members. We calculate implicit wage rates by summing income from these three types of sources, dividing by the total number of household members who work for wages, and dividing by 23 days * 8 hours = 184 hours per month. The median hourly wage rate in the 150 households with these income sources is 33 Ksh per hour; the average is 58 Ksh/hr. Field staff estimated that 35 Ksh per hour was the most common rate for unskilled manual labor, which fits within our calculated wage estimates.

Average food expenditure is 430 Ksh (5 USD) per household member per week, or a total of 14,924 Ksh (174 USD) per month. Household assets include a cell phone, bicycle, and radio, and most households own livestock. Using data on durable assets, electricity connections, sanitation, building characteristics, and cooking fuel, we construct a wealth index using principal component analysis (PCA) following Filmer and Prichett (2001) and Filmer and Scott (2012), and assign households to wealth quintiles. Although water supply variables are often included in wealth indices, we exclude them to avoid potential confounding with other explanatory variables. (Appendix A1.5 provides more details on the construction of the wealth index.)

Table 1: Household demographics

	Mean	Std Dev
Household size	5.62	2.2
Water collectors	1.72	1.5
Female respondent	0.79	0.4
Years of education of female (head of hh or spouse)	7.09	3.7
Has working elec. conn.	0.098	0.3
Total monthly income (Ksh)	46407.8	58831.3
Weekly food exp. per person (Ksh)	435.7	326.5

Notes: N=325.

What do people think about their current water sources? This is important not only to understand the site but also because these characteristics will be used as explanatory variables in the discrete choice analysis of the stated preference data. First, the majority know that drinking water from their current "primary source" poses some health risk (Table 2). Although one might think that water brought by a vendor is safer, respondents are aware that vendors often collect from the same unprotected sources. Water from public piped connections is also unsafe because of intermittent pressure and because some systems divert directly from a river without treating the water. Second, conflict is a salient feature of their water collection activity. Sixty-six percent of users of a public well say that using the source is likely or very likely to lead to conflict with their neighbors. Private well owners were asked a different question: "has sharing water from your well ever led to conflicts with your neighbors?" Although 27% said "yes", we assume in our analysis below that *using* your own private well does not risk conflict. We assume the same for people buying vended water. Third, although water is not always available from sources at convenient times, it is generally accessible. The majority of sources are open 12 hours per day, 7 days a week, or more. We categorize this as "good" availability in Table 2; see table notes for more details. Households who rely primarily on vended water are the most unsatisfied in this regard; forty percent said that service is "irregular" or "unreliable".

Table 2: Households' perceptions of their current "primary" water source

	Some Health Risk	Serious Health Risk	Conflict some-what likely	Conflict very likely	Good avail.	Fair avail.	Cloudy or brown color
Private well(78)	0.44	0.26	.	.	0.42	0.41	0.19
Vended(15)	0.73	0.20	.	.	0.33	0.27	0.40
Public well(122)	0.56	0.28	0.22	0.44	0.86	0.12	0.38
Public borehole(72)	0.28	0.10	0.24	0.25	0.56	0.42	0.14
Public piped conn(32)	0.47	0.06	0.38	0.03	0.50	0.41	0.22
Surface, other public(6)	0.00	0.67	0.33	0.50	0.83	0.17	0.33

Notes: The value in parentheses in the first column is the number of respondents who reported that this type of source was their primary source "overall, for most purposes"; e.g. 78 households reported a private well was their primary water source. **Health risks** refer to perceived risk from drinking water. "No" health risk is omitted from the table. **Conflict** refers to the likelihood that "there could be a conflict if you collect from this source in the dry season". Except for private wells and vended water, **availability** refers to the number of hours per week the source is open for collection; "good" is 12 hrs per day 7 days a week (84 hrs) or better. "Fair" is 24-83 hrs per week, and "Poor" is less than 24 hrs per week. For private wells and vended water, availability is "good" if the respondent said the reliability of water from the well (or vendor) is "very regular", "fair" if "regular", and "poor" if "irregular" or "unreliable".

Households spend significant economic resources in collecting water. Households purchasing water from sources away from the household pay approximately 2 Ksh per 20L "jerrican"[2] (equivalent to USD 0.31 per thousand gallons, or USD 1.16 per cubic meter), and water

[2] The term jerrican is commonly used to denote rectangular, hard plastic water storage containers, the vast

from vendors costs 10 Ksh per jerrican (Table 3). Households walking to get water reported that, on average, it took them 22 minutes to walk home from the source with a full container. These reported estimates are multiplied by 1.75 to get reported roundtrip walk times, to account for faster one-way trips with empty containers. Thirteen percent of households reported round-trip walking times over one hour. Households walking to get water reported that they spend one hour, on average, waiting to fill their container during an average week in the dry season. We do not know whether households are able to leave jerricans in line and spend the hour doing other tasks; our results below assume they do not.

Table 3: Distances (in minutes) and prices for current primary water source

	Roundtrip walking time[a]	Reported dry season wait times (mins)[b]	Price per 20L
Private well(78)	1	1	0.0
Vended(15)	.	1	9.7
Public well(122)	48	66	2.2
Public borehole(72)	24	51	2.2
Public piped conn(32)	26	54	2.1
Surface, other public(6)	85	68	3.0

Notes: [a] Roundtrip times are 1.75 times the reported one-way walk times with a full container and were estimated for households with private wells based on the reported distance (in meters) between the household and the well, assuming a walking speed of 2.75 kilometers per hour. [b] Wait times for private wells and vended water are assumed to be one minute for filling or the transaction; these were not reported by the household.

4 Choice experiment

After asking about the characteristics of the sources they could and do currently use, respondents were asked to imagine that two new hypothetical water source alternatives were available to them. The full translated text of the hypothetical scenario is given in Appendix A1.2. They were told that the water from these new sources would be "excellent and safe for drinking", that the new sources would be open at times convenient for them, and that using the new source would not cause any conflict with their neighbors. The only two attributes that varied between the two new options is the price charged per jerrican and the time it would

majority of which hold 20 liters of water.

take to collect water from the source (including time waiting and filling the container). The enumerator then showed the respondent the choice task card, explained the attributes associated with each hypothetical new water point, and asked if the respondent had any questions. An example choice task card, translated into English, is shown in Figure 1. Respondents were asked which of the three sources they would most and least prefer to use. The term "preferred to use" was intended to mean the source that the respondent would use exclusively as their primary water source and this is how the question was posed to respondents in the Meru language. We use the most and least-preferred data to construct a complete ranking of the two hypothetical choices and the respondent's current primary source.

Figure 1: Example choice card (translated into English)

	New water point A	**New water point B**	**Your current source**
Total time to walk to source, wait, fill container and return home	**10 minutes**	**5 minutes**	
Cost per 20L jerrican	**1 Ksh** per 20L jerrican	**0.25 Ksh** per 20L jerrican	

The experiment was based on a full factorial design of two three-level attributes: a price of 0.25, 1, or 3 Ksh and a total water collection time of 5, 10, or 30 minutes. These attribute levels were chosen to be lower than average current source prices and collection times so that they would be appealing to respondents. Choice tasks where either hypothetical alternative dominated the other on both time and cost were eliminated, leaving nine choice tasks. These were then divided into three blocks with three choice tasks each. Respondents were randomly assigned to blocks, and task order within the block was randomized. In addition to the three tasks from the block, all respondents were presented with a task (the one depicted in Figure 1) that included one source with the lowest time and lowest price and another source with the middle time and middle price. Because one of the two hypothetical sources dominated the other in both time and price, this task served as a simple comprehension check for the choice experiment. The task was also intended to determine whether the most attractive hypothetical source might tempt households with private wells. The full experimental design is provided in

Appendix Table A1.

Table 4: Patterns of respondent choices

	Ranked dominated choice higher	Didn't think carefully about SP exercise	Always chose status quo source
Private well(78)	0.04	0.00	0.67
Vended(15)	0.00	0.00	0.13
Public well(122)	0.08	0.02	0.07
Public borehole(72)	0.10	0.04	0.06
Public piped conn(32)	0.00	0.00	0.06
Surface, other public(6)	0.00	0.00	0.00
Total	0.06	0.02	0.21

Notes: The sample size is given in parentheses beside the description of current primary source. First column of results based on reported rankings for task where alternative B dominates A - see Figure 1 or Table A1. Second column is based on the enumerators' rating of how seriously the respondent took the choice task.

Did respondents understand the exercise and take it seriously? We begin with the comprehension check just described. Overall, only 24 respondents (6%) ranked the dominated alternative higher (Table 4). Immediately after the hypothetical exercise, we had enumerators report whether the respondent "thought carefully" about the choices. They felt that 76% of respondents thought "very carefully", and that only 8 respondents (2%) did not think carefully. Finally, 21% of respondents chose their current primary water source in all four choice tasks; not surprisingly, three-quarters of these 69 respondents had private wells at home. For other households that chose their current source, the hypothetical alternatives were in most cases better in all *observable* dimensions than their current source. Although this could indicate a lack of engagement in the task or status quo bias, it may also simply reflect preferences for their current water source in some other dimension that was not described in the hypothetical scenario. (We also asked respondents about the taste and color of the drinking water but omit them from our analysis because of correlations with the health risk variable). Section 5 examines how sensitive results are to excluding respondents who ranked a dominated alternative higher, did not appear to engage seriously, or chose a status quo of inferior observable quality despite not having a well at home.

4.1 Econometric estimation

We model the choice between the respondents' status quo water source and the two new hypothetical sources using a standard random utility framework (McFadden 1974). For brevity, we relegate the details of the model specification to Appendix A1.4. We rely on two econometric approaches: random parameter logit (RPL) and latent class multinomial logit. The random-parameters or "mixed" logit (Revelt and Train, 1998) specification allows us to exploit the panel nature of the repeated hypothetical choices to test for heterogeneity in preferences for distance and price, and thus the value of travel time. The RPL model builds on the simple multinomial logit (MNL), sometimes called conditional logit (McFadden, 1974), which assumes one population-level coefficient for each attribute and relies on the independence-of-irrelevant-alternatives (IIA) assumption. RPL models do not rely on the IIA assumption.

Logic and economic theory suggest that households, in comparing two sources that are the same in all other regards, should not prefer the source that is farther away or more expensive. In other words, the coefficients on price and time should be negative. Random-parameters models incorporate heterogeneity by estimating a fixed population-level coefficient β as well as a random disturbance σ_n around that β. This disturbance term is often assumed to be normally-distributed, which places no *a priori* sign restrictions on the individual-level coefficient $(\beta+\sigma_n)$ and can lead to models predicting that a certain fraction of respondents have *positive* cost or time coefficients. Researchers have avoided this problem by assuming a distribution for σ_n that is truncated or restricted to one domain, typically lognormal distributions. We tested a number of distributions that accomplish this, including lognormal, one-sided triangular, Rayleigh, and scaled exponential. Our main results assume σ_n is distributed one-sided triangular, which restricts the mean and standard deviation to be the same, for reasons we discuss in the Results section.

The first set of RPL results uses each of the four choices between hypothetical alternatives A and B and the respondent's current primary water source. We code the price and time attributes for the current primary source as continuous variables based on what respondents told us about those sources (Table 5). We assume that households with private wells face no financial cost for using that well, and impute the time using GIS and the reported distance from the home to the well (predicted roundtrip times are all less than 4 minutes and most are under 2 minutes). We use the reported wait times and assume it takes households with private wells one minute to fill their container[3]. Each of these characteristics is interacted with an alternate-specific constant that is equal to one if the respondent "opts out" of the hypothetical choices and stays with her primary source (Table 5). The coefficients on this interaction can be interpreted as increasing or decreasing the chance that the respondent opts out. For example, a respondent who reported that her current primary source is very unsafe to drink should be less likely to opt out than a respondent who thinks her current source is safe to drink, all else equal; the coefficient on the interaction should be negative. [4] We also estimate a model that uses the information contained in the complete ranking of sources.

[3]Households may value time spent traveling differently than time spent waiting, and may value lower variability in wait times. Although we observe travel and wait times separately for the household's current source, the hypothetical scenario combined the two. Any differences are not identifiable in our stated preference data.

[4]An alternate approach would be to treat these variables like price and time: respondents were told to assume that the new hypothetical sources were safe to drink, convenient and pose no risk of conflict, so one could assign them values for risk, conflict and availability that are all "good" (i.e. -1 for risk and conflict and 1 for reliability). This would induce extremely high correlations with ASC, however, since the hypothetical alternatives always have the same values.

Table 5: Description of primary and hypothetical source attribute variables

Variable	Description	Hypothetical Source Coding	Primary Source Coding
Time	Round trip walk time and waiting	5,10,or 30 minutes	1.75*one-way walk time[1] with full container + wait time[2]
Price	Price of 20 jerrican	Ksh 0.25,1 or 3	reported price per jerrican for primary source; 0 if doesn't pay
ASC	Alternate-specific constant	0	1
Health risk	Perceived risk from drinking water	N/A[3]	*Effects-coded*: =-1 if "no risk" = 0 if "some risk" = 1 if "serious risk"
Availability	Hours open and reliability	N/A[3]	*Effects-coded*: = -1 if less than 24 hrs/wk or "irregular" = 0 if 24-83 hrs/wk or "regular" = 1 if >=84 hrs/wk or"very regular"
Conflict	Potential for conflict from using source	N/A[3]	*Effects-coded*: = -1 if conflict "not likely at all" = 0 if conflict "somewhat likely" = 1 if conflict "very likely"

Notes: See notes for Table 2 for more details on health risk, conflict and availability variables. [1] Predicted walk times used in place of reported times where distance between home and primary source was observed in GIS. [2]Wait times as reported by households. [3] Health risk, availability and conflict are all assumed to be excellent for hypothetical sources, but these variables enter only as interactions with ASC to avoid collinearity problems.

The second econometric approach is a latent class multinomial logit, which uses the panel response data to partition respondents into c classes, where c is specified by the researcher (Roeder et al., 1999). We estimated latent-class models with c varying from 2 to 6 classes and chose models based on the best (lowest) Bayesian Information Criterion (BIC) score. We use a multinomial polytomous logit model to correlate household characteristics to class membership. All RPL and latent class models were estimated in NLOGIT5 (Greene, 2012); the multinomial polytomous logit model was estimated in Stata 12.1[5].

[5]We also attempted to estimate "scale" multinomial logit models that assume that heterogeneity in response patterns is due to individual-level differences in the error term, or "scale", rather than preferences. Intuitively, one can think of differences in scale as differences in response "noise" via factors such as how seriously respondents took the task, how well they understood the task, fatigue (from large numbers of choice sets), lexicographic preferences (i.e. always choose the alternative with the lowest price), or the use of unobserved heuristics to "solve" complicated choice tasks with large numbers of alternatives or attributes. Scale models would not converge on our dataset. We also analyzed the data using a "generalized" multinomial logit (Fiebig et al., 2010) that nests the

5 Results

5.1 Random parameter logit results

The top panel of Table 6 reports estimated coefficients (utility weights) for the mean (β) of randomly-distributed parameters as well as the ASC-interaction parameters that are modeled as non-random. The bottom panel shows the standard deviation of randomly-distributed parameters; significant coefficients here indicate that the preference heterogeneity among respondents is statistically significant. Price and time were modeled as one-sided triangular distributions to restrict them to be in one domain (here negative)[6]. This distributional assumption also restricts the mean and standard deviation to be the same, which is why the coefficients for means and standard deviations are always the same in Table 6. The ASC variable was modeled as normally-distributed.

Model A excludes households with private wells but includes respondents who enumerators rated as possibly not thinking carefully about the exercise, who made a preference error by ranking the dominated alternative higher, or who chose their current source on every task. Price and time are strongly significant, and the ASC is negative and statistically significant, indicating an unmodeled propensity to avoid the current primary water source. Stated differently: there are characteristics of the decision between the current primary source and either of the two hypothetical sources that are not captured by price and time.

random-parameters logit model and the scaled multinomial logit. A model using reported walk and wait times would not converge. It had a worse AIC and BIC score, however, than the corresponding RPL model. The scale parameter was not statistically significant, indicating overall that the RPL approach fits the data better.

[6]Models were estimated for three other distributional assumptions that restrict the price and time coefficients to be negative. Models with lognormally-distributed price and time would not converge (after multiplying by -1 to restrict them to the positive domain), and models assuming Rayleigh distributions also had inconsistent convergence. Models using a scaled exponential distribution converged and in general had lower log-likelihoods and BICs, but produced skewed distributions of VTT with means on the order of 120 Ksh per hr, or 350% of the unskilled wage rate of 35 Ksh/hr, and far higher than the VTT estimates from the simpler multinomial logit model. Kremer et al. (2011) also assume one-sided triangular distributions for distance in their RPL model (see Table VI, pg. 178).

Table 6: Random-parameters logit model results

	Model A	Model B	Model C (include private wells)	Model D (incl. wells and rank data)
Means				
Walk + wait time	-0.144***	-0.146***	-0.167 ***	-0.154***
(Mins)	(0.014)	(0.015)	(0.015)	(0.0089)
Price per 20L	-0.749***	-0.737***	-0.823***	-0.677***
(Ksh)	(0.087)	(0.088)	(0.082)	(0.0495)
ASC	-2.68**	-5.16***	-0.849	2.50***
	(1.64)	(1.87)	(0.972)	(0.563)
ASC * Reliability		3.21**	1.68**	1.80***
		(1.26)	(0.844)	(0.593)
ASC * Conflict		-1.07	-1.23*	0.276
		(0.96)	(0.727)	(0.487)
Standard deviations of random parameters				
Walk + wait time	0.144***	0.146***	0.167***	-0.154***
(one-sided triangular)	(0.014)	(0.015)	(0.015)	(0.0089)
Price per 20L	0.749***	0.737***	0.823***	-0.677***
(one-sided triangular)	(0.086)	(0.086)	(0.082)	(0.0495)
ASC	8.92***	8.58***	7.35***	
(normal)	(1.21)	(1.10)	(0.782)	
Households	247	247	325	325
Observations	978	978	1,288	1,288
Log Likelihood	-688	-686	-820	-1471
AIC	1384	1386	1652	2954
BIC	1404	1415	1683	2985
BIC (MNL)	1755	1758	2238	3823
Mean [Median] VTT	16.6 [15.8]	17.1 [16.4]	17.4 [16.4]	19.4 [19.3]
St. Dev. VTT	8.35	8.57	8.52	10.60
Mean VTT (MNL)	15.1	17.5	12.5	12.0

Notes: Standard errors in parentheses. * $p<0.10$, ** $p<0.05$ *** $p<0.01$. Simulated maximum likelihood used 500 Halton draws. Value of travel time (VTT) for the multinomial logit (MNL) model is calculated as $\beta_{time}/\beta_{price}$. Mean, median and standard deviation of the VTT for the RPL models refers to the empirical distribution of individually-calculated VTT estimates.

Model B adds two interaction terms with the ASC parameter and two observable characteristics of the current primary source: the reliability and potential for conflict in using the status quo source. The coefficient on the interaction with reliability is statistically significant and of the expected sign: respondents are more likely to select their current primary sources over the hypothetical alternatives when their current source is more reliable.[7] The coefficient on the interaction with the likelihood of conflict is of the expected sign but is not statistically significant. Although the log likelihood of Model B is slightly better than Model A (as would be expected from adding two additional explanatory variables), Model B performs worse on the two information criteria that penalize the model for these two additional parameters. The pairwise correlation between variables for health risk and conflict is statistically significant and large (0.43; the full correlation matrix is reported in Appendix A1.6), so models that include both of these variables simultaneously are suspect and were unstable in practice. A model that replaced the interaction on conflict with an interaction with the health risk of the current source produced very similar coefficient estimates for time and price, but a smaller, less negative ASC; neither the interaction with reliability nor risk were statistically significant (results available on request) [8].

Model C includes households with private wells. The coefficients on price and time both increase in magnitude, though their ratio is similar. The distribution on the ASC coefficient has a statistically significant spread but is now centered around zero: as expected, adding households with private wells adds observations where the current primary source is chosen more frequently. The interactions on both reliability and conflict are statistically significant. Model D, still including households with private wells, includes the preference information contained in the ranking of all three sources. Using this information implies respondents are somewhat more responsive to price and less responsive to distance, compared to Model A. The interaction with reliability increases in magnitude and significance, though the interaction with conflict is no longer different than zero. Finally, the pattern of significance is similar when

[7] Recall from Table 5 that reliability is effects-coded. For Model B, a respondent (call her A) with a "very regular" primary source (effects-coded=1), would have an overall mean ASC of -5.16 (population mean) + 3.21 (interaction coefficient) = -1.95. Respondent B with an "irregular" source (effects-coded=-1) would have an overall mean ASC of -5.16 (population mean) + (-1)(3.21) = -8.37. Respondent B is less likely to choose her current primary source than Respondent A.

[8] In general, the pattern of significance and sign with source characteristic variables interacted with ASC varied in a number of model estimates not reported. In models not shown, we also investigated replacing reported walking and wait times with predicted times from GIS (where possible), and median walking and waiting times by sublocation. The main results on the value of travel time did not vary substantially, though the interaction terms did.

dropping respondents who made a preference error or who were rated as not thinking about the task carefully, though the coefficients on price and time increase in magnitude, as expected (Appendix Table A5).

The bottom three rows of Table 6 report the distributional statistics for the implied individual-level estimates of the value of travel time savings. Because the triangular distributions restrict the mean and standard deviation to be the same, the means and medians are similar, and these are in turn relatively stable across the four model specifications, as well as a number of specifications not shown. They are also similar, as would be expected, to the single population-level VTT implied by the multinomial logit model, shown in the last row. The mean VTTs in Table 6 are 47%, 49%, 50%, and 55% of the unskilled manual wage rate of 35 Ksh per hour, and consistent with the "rule of thumb" discussed in the introduction.

Figure 2: Comparison of value-of-travel time estimates from RPL models

Notes: Respondents are ordered based on VTT results from Model C Table 6.

The distribution of predicted individual-level VTT estimates is reasonably consistent across the four models. Figure 2 orders respondents based on the implied VTT estimate from

Model C but reports individual-level estimates from all four models, as well as the latent class model discussed next. The model using the ranking data is less well correlated than the other three models. These VTT estimates are not correlated, however, with reported income, implied wage rates, the PCA-calculated wealth index score, education, the number of water collectors in the home, the age of the main water collector, and whether the main water collector earned wages. Pairwise correlations between each of the four predicted VTTs and these variables were small and not statistically-significant at the 10% level in all but two cases. The pairwise correlation between estimates from Model D and whether the main water collector was a man was statistically significant but small (-0.12). Households with more water collectors as measured in "adult equivalents", based on nutritional requirements from Collier et al. (1986), had lower VTT estimates from Model D (-0.09).

5.2 Latent class models

We fit a latent class multinomial logit model to the choice between the current primary source and the two hypothetical choices, but with no interactions on the ASC term. These models used data from all respondents, including those with private wells. The model does not require distributional assumptions for price or time, and relaxes the IIA assumption between but not within classes. A model with four classes had the best, lowest Bayesian Information Criteria among models with 2 to 6 classes. The first three panels of Table 7 presents the estimated coefficients, the implied VTTs, and the estimated class probabilities.

The model estimates that members in the first class – about one-third of respondents – were quite responsive to both price and time, and had a high implied value of travel time (49 Ksh per hour, or 140% of unskilled wages). The negative coefficient on ASC implies, as before, an unmodeled or unobserved propensity to avoid choosing their current primary source.

The second class is very responsive to the price of sources, but much less sensitive to the time cost, implying a very low class VTT (less than 1 Ksh per hr). The positive ASC indicates that – time and price equal– respondents are 'happy' with their primary source. The third and fourth classes were less responsive to both price and time, implying a VTT around 9 Ksh per hour, or roughly 25% of unskilled wages. The third class has a positive ASC coefficient while the fourth has a negative coefficient. Figure 2 plots these individual-level coefficients, which take one of four values. Respondents predicted to be in class 2 with a low VTT appear more likely to have a low predicted individual-level VTT from any of the four RPL models.

The bottom panel of Table 7 explores which characteristics of households, their current primary water sources, or their choices might be correlated with membership in the four classes. These summary statistics are calculated for the subset of respondents predicted to be in each class, determined by which of the four predicted probabilities is highest for that individual. Several patterns emerge. First, households in Class 1 (with the highest VTT) have higher mean and median reported incomes and higher wealth index scores than those in classes 2 and 3. Class 1 also has a higher fraction of respondents with private wells and not surprisingly the highest fraction of respondents who always chose their current source. Households in class 2 - with the lowest VTT - have the lowest mean income and are least likely to have a household member earning wages from full-time income. The pattern for the number of household members per water collector is less clear. If a water collector is collecting for fewer household members, one might expect her sensitivity to the time cost of each collection trip would be lower. This would be consistent with Class 3, which has the lowest number of the four classes, but not with Class 4, which has the highest collection "burden" but a similarly low sensitivity to time. We do not include household-level implied wage rates in the regression reported in Table 7 because it would drop the majority of households; recall that only 40% of households have wage income. The pair-wise correlation between the latent-class VTT and the calculated wage rates is statistically significant at the 5% level, though the coefficient is modest (0.19).

Table 7: Latent class multinomial logit: Model results and summary statistics by class

	Class 1	Class 2	Class 3	Class 4
Price	-3.009**	-3.086***	-0.1544**	-0.7097***
Time	-2.498**	-0.0396***	-0.0236***	-0.1018***
ASC	-5.673*	2.908***	2.447***	-3.647***
VTT (Ksh/hr)	49.8	0.8	9.2	8.6
Estimated latent class probabilities	(34%)	(19%)	(15%)	(32%)
Respondents predicted in class[a]	142	50	28	105
Primary source characteristics:				
Private well (24% overall)	35%	10%	14%	18%
Vended water (4.6% overall)	5.6%	4.0%	3.6%	3.8%
Reported one-way walk time (mins)	21	24	15	24
Reported wait time (mins)	30	65	47	49
Using source likely or very likely to lead to conflict (41% overall)	32%	52%	36%	51%
Drinking poses "some" or "serious" health risk (67% overall)	65%	74%	57%	69%
Household characteristics				
Household members per water collector[b]	4.2	3.8	3.2	3.4
Respondent has primary education (53% overall)	51%	40%	57%	61%
Household has income from full-time employment (12.9% overall)	12.7%	6.0%	10.7%	17.1%
Monthly income (mean)	51,615	34,196	39,448	47,408
[median]	[39,230]	[26,390]	[30,550]	[33,750]
Median wealth score (PCA) (less negative=higher wealth)	-0.30	-0.46	-0.71	-0.31
Choice task characteristics				
Chose dominated (6% overall)	5%	10%	14%	4%
Always chose current source (21% overall)	34%	14%	18%	9%

Notes: * p<0.10, **p<0.05 ***p<0.01. [a] Respondents were assigned based on which predicted class probability was highest for that respondent. [b] Households with private wells were not asked about who was a "water collector" and four households who rely on vended water reported no water collectors; we assume one collector for each of these households. Value of travel time (VTT) is constant within each class and is calculated as $\beta_{time}/\beta_{price}$. A model with 4 classes had the lowest (best) BIC score of models fitted with 2-6 classes; more than 6 classes would not reach convergence. The model presented used 1288 observations from 325 respondents, achieved a log-likelihood of -765, and had an AIC and BIC of 1560 and 1637.

Table 8: Explaining class membership: multinomial (polytomous) logit model

Variable	**Class 1**	**Class 3**	**Class 4**
Private well	1.49 (0.67)**	0.972 (0.945)	1.74 (0.715)**
HH members per water collector	-0.048 (0.088)	-0.189 (0.137)	-0.166 (0.0947)*
Income quintile	0.211(0.124)*	0.067 (0.176)	0.198 (0.128)
Health risk (effects-coded)	-0.410 (0.240)*	-0.362 (0.331)	-0.220 (0.242)
Always chose current source	0.228 (0.574)	-0.133 (0.791)	-1.437 (0.674)**
Ranked dominated alternative higher	-0.711(0.639)	0.418(0.741)	-0.857 (0.716)
Constant	0.282(0.490)	-0.277 (0.69)	0.746 (0.500)

Notes: N=325. Standard errors in parentheses. Test statistics for likelihood ratio test (18 df) is 50.3. The probability that a model with only class constants performs as well as this model: p=0.0001.

To test these relationships statistically, we estimated a multinomial (polytomous) logit regression (Table 8). The model fits a maximum likelihood model for a discrete dependent variable (in our case, the class to which the respondent is predicted to belong) when there are multiple outcomes for the dependent variable that have no meaningful ordering. (Note this is different than the multinomial logit model discussed earlier, which is often called the conditional logit.) Compared to respondents predicted to be in Class 2 (the omitted category), respondents in Class 1 are more likely to use a private well and to be in a higher income quintile, and less likely to rate their current water source as posing a health risk. Similarly, respondents in Class 4 are more likely than those in Class 2 to own wells, have a lower water collection burden (fewer members per collector), and are less likely to have chosen their current source in all four hypothetical tasks. Classes 2 and 3 are more similar; none of the independent variables in Table 8 predicts membership in Class 3 compared to Class 2.

6 Conclusions

Our results present a mixed picture. On one hand, the mean and median estimates of the value of travel time derived from the simple hypothetical exercise are in line with the "rule of thumb" of using 50% of the unskilled wage rate. These results are robust to the model specifications reported here as well as several not reported. Overall, our results add to the relatively limited knowledge about valuing time in rural areas of poor countries, and support the 50% rule.

We present the first (to our knowledge) individual-level VTT estimates in a setting like ours using a random-parameters logit framework as well as a latent class multinomial logit approach. How confident are we this heterogeneity matters? Results on price and time – the two main attributes of the choice experiment - are stable and consistently statistically significant in models reported here and a number of others (including with scaled exponential and normal distributions) not reported. In all four models, the random parameters approach fits the data better than a simpler multinomial logit model: moving from the MNL to the RPL model improved BICs and log-likelihoods approximately 30% in all four models. The individual-level predicted VTTs from the RPL model are not, however, well correlated with observables such as income, a wealth index, wage labor, or the number of water collectors in a household. An agnostic latent class model divided our respondents into four classes, with one class valuing time very highly, one hardly at all, and two classes in between. Membership in these groups was driven primarily by whether the household's primary water source is a well at home, but class membership was also influenced (encouragingly) by income quintile and the household's "demand" for water collectors (the number of household members per water collector).

Why might the relationship between VTT estimates and socioeconomic characteristics be weak? We cannot rule out that respondents did not think carefully about the exercise and their own current water source options, but, supplementing our robust results on price and time with reports from our enumerators, this seems less likely. Households may also have a different social and practical conception of "time" than those in urban areas in Kenya or in wealthier countries, and may have difficulty both reporting their own current time burdens from water collection and imagining a reduced burden from collecting from the two new sources. The ability to convert time into money is also limited (Larson, 1993) – only 39% of households in our survey had a member who worked for wages – and highly dependent on the seasonality of farm income.

The stated preference approach reported here could nevertheless be quite useful in empirical research on valuing time use in rural areas of poor countries. It is relatively simple to design and implement, and could be applied to any of the many settings where households are still walking to draw water as well as collect firewood. Unlike other stated preference experiments, strategic bias seems less likely in respondents' answers[9]. The full factorial experimental design could be replicated by changing only the attribute levels to make them appropriate to the study site. We analyzed data using NLOGIT, a program that is less widespread that Stata or SAS but which has a long history in discrete choice analysis. There is now a Stata routine (*mixlogit*) to fit RPL models. Where primary data is already being collected, we estimate that adding this module would add ten minutes at most to the survey length.

References

Alpizar, Francisco and Fredrik Carlsson, "Policy implications and analysis of the determinants of travel mode choice: An application of choice experiments to metropolitan Costa Rica," *Environment and Development Economics*, 2003, *8*, 603–619.

Asthana, A N, "Where the water is free but the buckets are empty: demand analysis of drinking water in rural India," *Open Economies Review*, 1997, *8* (2), 139–149.

Boardman, Anthony, David H Greenberg, Aidan R Vining, and David L Weimer, *Cost-benefit analysis: concepts and practices*, 4th ed., Upper Saddle River, NJ: Prentice Hall, 2010.

Collier, P., S. Radwan, and S. Wangwe, *Labour and Productivity in Rural Tanzania*, Oxford UK: Clarendon, 1986.

Dissanayake, Dilum and Takayuki Morikawa, "Household Travel Behavior in Developing Countries: Nested Logit Model of Vehicle Ownership, Mode Choice, and Trip Chaining," *Transportation Research Record*, 2002, *1805* (02), 45–52.

Fiebig, Denzil G., Michael P. Keane, Jordan Louviere, and Nada Wasi, "The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity," *Marketing Science*, May 2010, *29* (3), 393–421.

Filmer, Deon and Kinnon Scott, "Assessing Asset Indices," *Demography*, 2012, *49* (April), 359–392.

[9]Strategic bias may show up in our experiment if respondents really wanted to send a signal to policymakers that they wanted the new hypothetical sources built by always choosing the hypothetical source. In this case, one might see only the ASC coefficient, and not the price and time of the alternatives, statistically significant. Also, in models not reported but available on request, we examined only the choice between the two hypothetical alternatives A and B, and price and time remained statistically significant, of similar magnitude, and implied similar mean VTTs. Also, our scenario made clear that cost-recovering prices would be a necessary feature of new handpumps, so households who were not willing to pay for more convenient water sources should have little incentive to overstate demand.

— **and Lant Prichett**, “Estimating Wealth Effects Without Expenditure Data or Tears: An application to educational enrollments in states of India,” *Demography*, 2001, *38* (1), 115–132.

Greene, William H, *NLOGIT Version 5 Reference Guide*, Plainview NY, USA and Caste Hill, NSW, Australia: Econometric Software, Inc., 2012.

Jeuland, Marc, Marcelino Lucas, John Clemens, and Dale Whittington, “Estimating the private benefits of vaccination against cholera in Beira, Mozambique: A travel cost approach,” *Journal of Development Economics*, March 2010, *91* (2), 310–322.

Kremer, Michael, Jessica Leino, Edward Miguel, and Alix Peterson Zwane, “Spring cleaning: Rural water impacts, valuation, and property rights institutions,” *Quarterly Journal of Economics*, 2011, *126* (1), 145–205.

Larson, Douglas, “Separability and the Shadow Value of Leisure Time,” *American Journal of Agricultural Economics*, 1993, *75*, 572–577.

Liu, Gang, “A behavioral model of work-trip mode choice in Shanghai,” *China Economic Review*, 2007, *18* (4), 456–476.

McFadden, Daniel, “Conditional logit analysis of qualitative choice behavior,” in P Zarembka, ed., *Frontiers of Econometrics*, New York, NY: Academic Press, 1974.

Revelt, D and Kenneth Train, “Mixed logit with repeated choices: Households’ choices of appliance efficiency level,” *Review of Economics and Statistics*, 1998, *80* (4), 647–657.

Roeder, Kathryn, Kevin G. Lynch, and Daniel S. Nagin, “Modeling uncertainty in latent class membership: A case study in criminology,” *Journal of the American Statistical Association*, 1999, *94* (447), 766–776.

Train, Kenneth, *Discrete Choice Methods with Simulation*, New York,NY: Cambridge University Press, 2003.

Von Wartburg, Markus and William G Waters, “Congestion externalities and the value of travel time savings,” in Anming Zhang, Anthony E Boardman, David Gillen, and William G Waters, eds., *Towards Estimating the Social and Environmental Costs of Transport in Canada: A Report for Transport Canada*, 2004, chapter 2.

Walker, Joan L., Jieping Li, Sumeeta Inivasan, and Denis Bolduc, “Travel demand models in the developing world: correcting for measurement errors,” *Transportation Letters: The International Journal of Transportation Research*, 2010, *2*, 231–243.

Waters, William G., “Values of travel time savings in road transportation project evaluation,” in David A Hensher, Jenny King, and Tae Hoon Oum, eds., *World Transport Research: Proceedings of the 7th World Conference on Transport Research*, New York: Elsevier, 1996.

Whittington, Dale, Xinming Mu, and Robert Roche, “Calculating the value of time spent collecting water: Some estimates for Ukunda, Kenya,” *World Development*, 1990, *18* (2), 269–280.

World Health Organization and UNICEF, "Progress on Drinking Water and Sanitation: 2014 Update," Technical Report, Joint Monitoring Programme 2014.

Appendix Materials

A1 Appendix

A1.1 Sampling

Our fieldwork took place in Meru County, Kenya. The most recent census in 2009 estimates there are 320,616 households in an area amounting to 6,936 square kilometers, giving an estimated population density of 196 persons per square kilometer. The county has a 12 percent urban population compared to a national average of about 32 percent (Kenya Open Data Survey, 2014). The elevation is approximately 5,000 feet and average annual temperatures range from 62-69 degrees F. Considered one of the most fertile parts of Kenya, this agricultural area produces staple crops, such as wheat, potatoes, and maize, as well as cash crops, including tea, coffee, and bananas. Rice is sold for 85 Ksh (1 USD) per kilogram while the price of maize is 30 Ksh (0.35 USD) per kilogram (or 2.2 pounds). Average annual rainfall is fifty-four inches and there are a variety of surface and ground water sources.

We sampled households in four "sublocations" in the Tigania West "location" within Meru County: Kianjai, Mutionjuri, Machako and Nairiri. Although Meru County is in the top quarter of Kenya's income distribution, Tigania West has many poor households which may represent the entire income distribution in Kenya somewhat better. According to the 2009 census, the populations of these sublocations were 1102, 1056, 337 and 398 households in Kianjai, Mutionjuri, Machako and Nairiri respectively.

The field team selected households by using access roads and paths as transect lines. Households were then randomly selected on either side of these paths for interview based on pre-determined skip patterns. Since our target sample was 400 households and the most recent census indicated 3,005 households in these four sublocations, we targeted approximately 13% of the population in each of these sublocations, or every fifth household. In 23 sampled households, the respondents in the household were unavailable so that call backs had to be scheduled. In 15 of these 23, an interview was later completed. The remainder were replaced after three unsuccessful attempts. Six households declined to be interviewed. This means that of 402 households contacted, 387 were interviewed giving a response rate of 96%. The final sample sizes by sublocation are given in Table 2.

Table A1: Interviews conducted and total number of households in each sublocation

Sublocation	Households interviewed	Total households in 2009 Census
Kianjai	141	1091
Mutionjuri	129	992
Machaku	44	341
Nairiri	74	581
TOTAL	388	3005

A1.2 Hypothetical scenario

The full text of the hypothetical scenario is:

"Now I would like you to imagine that a group is planning to install several new water points in your area to improve your access to water. The group could be the government or it could be a non-governmental organization. These water points could be boreholes or public standpipes from the piped network. If they install only a few water points, people might have to walk further and wait longer to collect water. If they install more, people might walk shorter distances and have to wait less. Installing these water points is expensive, however. Suppose <the group> will need to charge people who use the water points to recover their costs and properly maintain the water points. If they install more points, they may need to charge more per jerrican.

You just told me that the primary source for most purposes right now was <primary source from previous question>. In addition to that source, I want you to imagine you have two new water points available for you to use. You should assume that quality of the water from the new water point is excellent and safe for drinking. You should also assume that the reliability of the new water point would be excellent: it would always have good pressure and you could collect from it whenever it is convenient for you. Finally, you should assume that using the source would not cause any conflict with other water users.

The two new water points differ only in the cost you would have to pay per jerrican, and the total amount of time it would take you to walk to the source, wait, fill your container and return. Here is the first task I would like you to think about.

If these three sources were available to you right now, which source would you most prefer to use? Remember that the two new sources have excellent quality and reliability, and using them would not cause conflict. Which source would you least prefer to use?"

A1.3 Full experimental design

Figure A1: Full design of choice experiment

Task	Source A		Source B	
	Price (Ksh per 20L)	Time (minutes)	Price (Ksh per 20L)	Time (minutes)
11	0.25	10	1	5
12	0.25	30	1	10
13	3	5	1	30
21	0.25	10	3	5
22	0.25	30	3	5
23	3	10	0.25	30
31	0.25	30	1	5
32	3	5	1	10
33	3	10	1	30
99	1	10	0.25	5

Notes: Blocks are indicated by the leading digit of the task number. Card 99 was answered by all respondents. A respondent in block 1 would answer tasks 11, 12, 13 and 99.

A1.4 Discrete choice modeling

Our underlying theoretical framework is random utility theory, which decomposes the utility U of using a particular water source into observable and unobservable components [10]. In our setting, $n = 325$ households choose from $j = 3$ different alternative water sources – their current primary source and the two new hypothetical sources. Each alternative source has observable source characteristic in the vector $\mathbf{X}$ that we expect provide utility or disutility from using the source. The most important of these attributes for our purposes are the distance in minutes to the source and cost per 20L from using the source, although characteristics such as availability of the source, safety of the water for drinking, potential for conflict, etc. go into the vector X. An indicator variable ASC that tracks whether the respondent is choosing her current primary source is also in X. Preferences for these each of these attributes is estimated in the parameter vector β. Like any repeated discrete choice experiment, our data resemble a panel, with $t = 4$ choice occasions or tasks. Characteristics of the household which may influence the choice of sources (i.e. tastes for safe water proxied by education, opportunity cost of time proxied by income or wage labor) enter through the vector z (and corresponding taste parameter vector θ), though these characteristics are constant across choice tasks. Remaining unobservable factors that influence source choice are in the error term ϵ_{njt}. The utility of alternative j in choice task t for person n is:

$$U_{njt} = \beta_n' x_{njt} + \theta' z_n + \epsilon_{njt} \tag{1}$$

The multinomial logit (also called conditional logit) model finds estimates for β that best fit the observed choice probabilities to ones estimated with equation 5. The choice probabilities have a closed-form solution and do not require simulated maximum likelihood. The

[10]This sections parallels the basic notational approach in Fiebig et al. (2010) but also draws from Train (2003).

model assumes one population-level average preference (hence β not β_n). Because θz_n appears in both the numerator and denominator, socioeconomic characteristics fall out of the MNL model unless they are interacted with choice-varying characteristics. The probability of observing that alternative j is chosen is:

$$P(j|X_{nt}) = \frac{exp(\beta' X_{njt})}{\sum_j exp(\beta' X_{nkt})} \tag{2}$$

The random parameters formulation relaxes the IIA assumpion and identifies individual-specific preferences as random, person-specific deviations η_n from the population mean preference β. The utility function now becomes:

$$U_{njt} = (\beta + \eta_n)x_{njt} + \theta' z_n + \epsilon_{njt} \tag{3}$$

The researcher specifies the distributional form for η_n, often multivariate normal with mean zero and variance-covariance structure of Σ. When theory restricts coefficients to be positive or negative, one can choose a distributional assumption that ensures that $(\beta + \eta_n)$ falls in that domain. In our application, we want to restrict both time and price to have a negative effect on the probability of choosing a source, and use a one-sided triangular distribution to achieve this. Other distributional assumptions are discussed in the text.

Because the random parameters formulation does not have a closed form solution, it is estimated with simulated maximum likelihood (Equation 4). The model searches for values of population-mean β as well as the mean of the distribution for η that best fits the predicted probabilities to the observed choice probabilities (i.e. the highest log-likelihood). The model takes D draws, each η^d, from the distributional assumption for η, estimates β from the simpler conditional logit expression for each draw, and averages the likelihood over D draws. (Estimates reported in this paper use D=500). This process repeats until a convergence threshold is reached (the log-likelihood does not improve). Again, person-specific characteristics that do not vary across choices drop out unless they are interacted with a choice-varying attribute.

$$P(j|X_{nt}) = \frac{1}{D} \sum_{d=1}^{D} \frac{exp[(\beta + \eta^d)X_{njt}]}{\sum_{k=1}^{3} exp[(\beta + \eta^d)X_{nkt}]} \tag{4}$$

The latent class multinomial logit models heterogeneity in preferences in a different manner. Rather than trying to estimate person-specific preferences (i.e. $(\beta + \eta_n)$), the model identifies C "latent" classes of respondents with similar preferences β_c. The model is a system of C multinomial logits.

$$P(j|class = c) = \frac{exp(\beta_c X_{njt})}{\sum_j exp(\beta_c X_{nkt})} \tag{5}$$

A1.5 Wealth Index

We construct a wealth index using principal component analysis (PCA) following Filmer and Prichett (2001) and Filmer and Scott (2012). Data on durable assets, electricity connection, sanitation, number of rooms and number of buildings, and main cooking fuel were included (see Table A2). Although water-related variables are often included in wealth indices constructed in this manner, we exclude them to avoid potential confounding with explanatory models in the main paper. All variables were converted to either dummy (0/1) or continuous variables. We had only two instances of missing observations. One respondent left blank any information about her ownership of livestock; we assume zero for this observation. A second respondent did not report the number of buildings in the compound; we assume it is one.

The first column of Table A2 reports the first principal component from the PCA analysis, which corresponds to the underlying latent variable of wealth. This first principal component had an estimated eigenvalue of 3.54, explaining 15.4% of variation in these 22 variables. In the case of binary variables, this score can be interpreted as the marginal change in the household's wealth score by moving from not owning the asset to owning (for example, owning a cell phone increases the household's wealth score by 0.221). Similarly, the three percent of housholds with no on-site sanitation option have a wealth score that is 0.163 lower than those with on-site sanitation.

The distribution of predicted wealth scores is relatively smooth and normally-distributed (Figure A2). Households are ordered on this predicted score and divided into five equal quintiles of 77 or 78 households each; the breakpoints in scores for each quintile are shown in the figure as vertical red lines. The remaining columns of Table A2 display the summary statistics for each of the component variables by the predicted quintile of wealth. For example, 71% of those in the lowest wealth quintile own a mobile phone, while all households in the fourth or fifth (highest) quintile own mobile phones. The results display face validity for the wealth index, with some small exceptions. Those in the lowest quintile own an average of 0.41 sheep, while those in the wealth quintile just above them own 0.19 sheep. There are similar patterns of non-monotonicity for owning a cart, owning a radio, owning a vehicle, and no sanitation at home.

Figure A2: Distribution of factors scores for wealth index

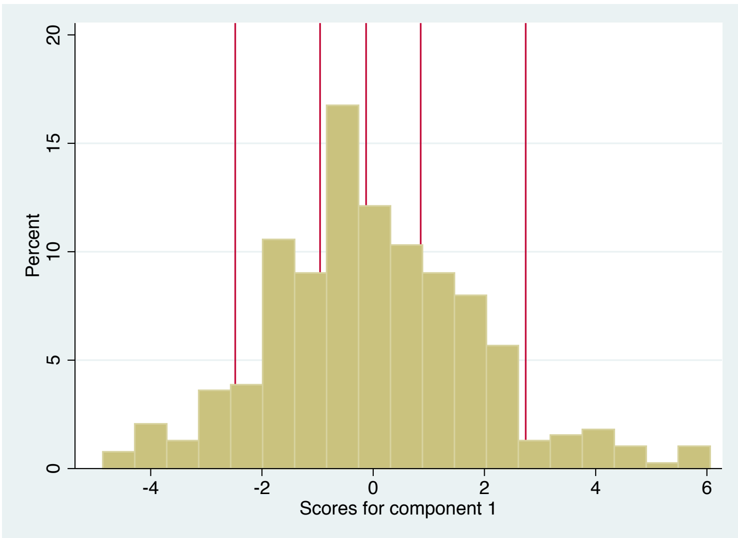

Table A2: Factor scores and descriptive statistics of components of the wealth index, by predicted wealth quintile

	Factor Score	Lowest	Second	Middle	Fourth	Highest	All
Own cell phone	0.221	0.71	0.97	0.99	1.00	1.00	0.93
Own bicycle	0.257	0.36	0.69	0.83	0.91	0.99	0.76
Own cart	0.158	0.05	0.04	0.09	0.27	0.35	0.16
Own radio	0.217	0.50	0.79	0.92	0.88	1.00	0.82
Own TV	0.289	0.05	0.19	0.30	0.62	0.79	0.39
Own motorbike	0.190	0.01	0.05	0.06	0.14	0.36	0.13
Own vehicle	0.206	0.00	0.01	0.04	0.03	0.27	0.07
Num. cattle	0.307	0.73	1.60	1.82	2.54	3.87	2.11
Num. goats	0.108	0.96	1.29	2.40	1.85	2.65	1.83
Num. sheep	0.128	0.41	0.19	0.42	0.96	1.27	0.65
Num. chickens	0.231	1.85	3.91	5.61	7.97	10.00	5.86
Own home	0.077	0.95	0.95	0.97	0.99	1.00	0.97
Has working elec. conn.	0.210	0.01	0.03	0.05	0.10	0.36	0.11
Num bedrooms	0.261	1.42	1.65	1.96	2.51	2.78	2.06
Num buildings	0.301	3.12	3.94	4.51	4.76	6.26	4.51
Acres land owned	0.281	0.95	1.07	1.60	1.92	4.47	2.00
No sanitation at home	-0.163	0.15	0.01	0.00	0.00	0.00	0.03
Owns non-shared toilet	0.190	0.60	0.79	0.92	0.94	0.97	0.85
Ventilated pit latrine	0.259	0.04	0.08	0.13	0.35	0.57	0.23
Cook w/ elec	0.054	0.00	0.00	0.01	0.01	0.03	0.01
Cook w/ biomass	-0.160	0.35	0.15	0.13	0.06	0.01	0.14
Cook w/ wood	0.160	0.58	0.78	0.82	0.88	0.96	0.80
Cook w/ charcoal	-0.065	0.08	0.06	0.04	0.04	0.00	0.04

Notes: N=387. Each quintile has 77 or 78 households.

A1.6 Correlation between independent variables

Table A3: Correlation coefficients *excluding* households with private wells

	(1) price	time_rep	time_med	etaste	color	erisk	eavail	econflict
price	1							
time_rep	0.0369	1						
time_med	0.0257	0.687***	1					
etaste	-0.177**	-0.142*	-0.0195	1				
color	0.0472	0.129*	0.0291	-0.462***	1			
erisk	0.238***	0.251***	0.185**	-0.451***	0.452***	1		
eavail	-0.226***	0.129*	0.195**	0.0556	-0.0682	-0.0183	1	
econflict	-0.00155	0.386***	0.290***	-0.263***	0.276***	0.430***	0.0622	1

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

Notes: Price is price per 20L jerrican. *Timerep* uses reported walking times, including times predicted from GIS where possible, and reported wait times; *timemed* uses median walk times (by sublocation) and median wait times (by source). *etaste* is effects-coded and equal to 0 if "normal" or "varies", -1 if "poor" and 1 if "sweet". *color* is a dummy variable equal to 1 if color is "brown" or "cloudy", 0 if "clear". *erisk* is equal to -1 "no risk" from drinking water, 0 if "some risk" and 1 if "serious risk". *avail* is -1 if hours open per week is less than 24, 0 if 24-83, and 1 if 84 or more. *conflict* is -1 if conflict from using source is "not likely at all", 0 if "somewhat" likely, and 1 if "somewhat likely".

Table A4: Correlation coefficients *including* households with private wells

	(1) price	time_rep	time_med	etaste	color	erisk	eavail	econflict
price	1							
time_rep	0.257***	1						
time_med	0.273***	0.775***	1					
etaste	-0.116*	-0.0814	0.0196	1				
color	0.0791	0.147**	0.0733	-0.397***	1			
erisk	0.162**	0.163**	0.105	-0.395***	0.381***	1		
eavail	-0.0449	0.219***	0.272***	0.0914	-0.0448	-0.0643	1	
econflict	0.194***	0.520***	0.461***	-0.188***	0.263***	0.313***	0.156**	1

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

Notes: Price is price per 20L jerrican. *Timerep* uses reported walking times, including times predicted from GIS where possible, and reported wait times; *timemed* uses median walk times (by sublocation) and median wait times (by source). *etaste* is effects-coded and equal to 0 if "normal" or "varies", -1 if "poor" and 1 if "sweet". *color* is a dummy variable equal to 1 if color is "brown" or "cloudy", 0 if "clear". *erisk* is equal to -1 "no risk" from drinking water, 0 if "some risk" and 1 if "serious risk". *avail* is -1 if hours open per week is less than 24, 0 if 24-83, and 1 if 84 or more. *conflict* is -1 if conflict from using source is "not likely at all", 0 if "somewhat" likely, and 1 if "somewhat likely".

A1.7 Sensitivity analysis

Table A5: Random-parameters logit model results - dropping 23 respondents either rated as not thinking carefully about the exercise and those who ranked the dominated alternative higher

	Model A	Model B	Model C (include priv. wells)	Model D (A vs. B only)
Means				
Walk + wait time	-0.165***	-0.170***	-0.190 ***	-0.202***
(Mins)	(0.0169)	(0.018)	(0.018)	(0.0184)
Price per 20L	-0.847***	-0.832***	-0.924***	-0.957***
(Ksh)	(0.097)	(0.096)	(0.093)	(0.093)
ASC	-4.06**	-6.58***	-1.09	
	(2.07)	(2.14)	(1.17)	
ASC * Reliability		3.66***	2.04*	
		(1.16)	(1.17)	
ASC * Conflict		-1.19	-1.17	
		(1.01)	(0.830)	
Standard deviations of random parameters				
Walk + wait time	0.164***	0.170***	0.190***	-0.202***
(one-sided triangular)	(0.0169)	(0.018)	(0.018)	(0.018)
Price per 20L	0.847***	0.832***	0.924***	-0.957***
(one-sided triangular)	(0.0975)	(0.096)	(0.093)	(0.093)
ASC	10.57***	10.22***	8.28***	
(normal)	(1.48)	(1.40)	(0.956)	
Households	227	227	302	302
Observations	899	899	1,198	1,205
Log Likelihood	-618	-616	-742	-624
AIC	1244	1244	1495	1251
BIC	1263	1273	1526	1261
Mean [Median] VTT	17.1 [15.9]	17.7 [16.7]	17.8 [16.6]	19.2 [19.5]
St. Dev. VTT	8.89	9.17	9.04	10.3
Mean VTT (MNL)	16.2	18.8	12.9	12.5

Notes: Standard errors in parentheses. * p<0.10, **p<0.05 ***p<0.01. Simulated maximum likelihood used 500 Halton draws. Value of travel time (VTT) for the MNL model is calculated as $\beta_{time}/\beta_{price}$. Mean, median and standard deviation of the VTT for the RPL models refers to the empirical distribution of individually-calculated VTT estimates.

Table A6: Random-parameters logit model results: replace reported walk times with GIS predictions where possible

	Model A	Model B	Model C (include priv. wells)
Means			
Walk + wait time	-0.135***	-0.135***	-0.164 ***
(Mins)	(0.0125)	(0.012)	(0.144)
Price per 20L	-0.730***	-0.707***	-0.844***
(Ksh)	(0.085)	(0.0804)	(0.084)
ASC	-0.992	-4.37***	-2.23**
	(0.844)	(1.36)	(1.10)
ASC * Health Risk		-0.636	0.948
		(0.705)	(0.690)
ASC * Reliability		3.61***	4.11***
		(1.75)	(1.20)
ASC * Conflict likely		-0.951	-2.14***
		(0.634)	(0.600)
Standard deviations of random parameters			
Walk + wait time	0.135***	0.135***	0.164***
(one-sided triangular)	(0.0125)	(0.012)	(0.014)
Price per 20L	0.730***	0.707***	0.844***
(one-sided triangular)	(0.084)	(0.0804)	(0.084)
ASC	8.68***	9.08***	10.72***
(normal)	(0.959)	(1.05)	(1.15)
Households	247	247	325
Observations	982	982	1,292
Log Likelihood	-695.3	-690.8	-817
AIC	1399	1396	1649
BIC	1418	1430	1686
Mean [Median] VTT	17.0 [15.4]	17.0 [15.7]	17.0 [15.8]
St. Dev. VTT	11.3	9.42	8.84
Mean VTT (MNL)	14.9	16.6	12.1

Notes: Standard errors in parentheses. * p<0.10, **p<0.05 ***p<0.01. Simulated maximum likelihood used 500 Halton draws. Value of travel time (VTT) for the MNL model is calculated as $\beta_{time}/\beta_{price}$. Mean, median and standard deviation of the VTT for the RPL models refers to the empirical distribution of individually-calculated VTT estimates.