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RESEARCH ARTICLE

Measuring the welfare effects of forests: an application of the travel cost model

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Abstract

In this paper, a travel cost model was applied to the case of firewood collection to assess how the inclusion of household fixed effects and how assumptions regarding conditions in the local labor market impacted resulting welfare estimates. To assess these impacts, a unique household panel data set from Kagera, Tanzania was used. It was estimated that, under the assumption of constrained labor markets, households in the Kagera region of Tanzania are willing-to-pay, on average, $120 per year (2016 USD) for access to local forests. These estimated figures were nearly 50 per cent higher when household fixed effects were excluded and nearly 10 per cent higher under the assumption of perfect labor markets. In addition, these results support previous research showing that, in many developing countries, households' demand for firewood is inelastic and that households would be willing to spend a significant amount of their resources on forest access.

Keywords: travel cost; agricultural production; development; environment

JEL classification: Q56; O13

1. Introduction

Ecosystem services, and measuring the value of ecosystem services to local populations, have become increasingly popular areas of research over the last two decades. In particular, a large body of research has focused on the ecosystem service value of forests, especially in developing countries. This strong focus on forests is relevant for both economic development and environmental conservation. From a development perspective, the Food and Agriculture Organization (2017b) estimates that globally 2.4 billion people rely on woodfuel to cook their food or to heat their homes and that over 700 million women are engaged in some form of woodfuel collection. In Africa, over two-thirds of all households rely on woodfuel as their main source of energy (Food and Agriculture Organization of the United Nations, 2017b). From a conservation perspective, forests are estimated to absorb the same amount of CO_2 as oceans – or 30 per cent of global CO_2 emissions (Bellassen and Luyssaert, 2014) – yet annually the world continues to lose roughly 3 million hectares of forest (Food and Agriculture Organization of the United

Nations, 2017a). The successful management of forests as a natural resource is significant from both a livelihood and a carbon emissions perspective. These management efforts are especially important in Africa, which continues to have one of the highest rates of deforestation globally and where a large segment of the population relies on forest products for daily household needs.[1]

The oversized benefits of forests are recognized worldwide; as of 2015, Denmark, the European Union, Japan, Luxembourg, Norway, and Spain have pledged nearly US$270 million to support the UN-REDD program (UN–REDD Programme, 2015). Efforts to curb deforestation, however, must fully incorporate the non-market private livelihood losses that could result from these programs. To that end, the World Bank Institute has published an entire 262-page manual on estimating the opportunity costs of the United Nations' Reducing Emissions from Deforestation and Degradation (UN-REDD) program (World Bank Institute, 2011). While measuring the opportunity costs of foregone deforestation is relatively straightforward when both the deforestation activity and the alternative activity take place in the marketplace, it is much more complex when one of the activities takes place outside of the market.

Most notably, understanding the importance of forest access for the collection of nontimber forest products is critically important in many developing countries, and this activity often occurs outside of formal markets. Angelsen *et al.* (2014) found that, across 24 developing countries, forest income from natural forests made up, on average, over one-fifth of total household income. To date, many studies that have focused on understanding how changes in forest access or forest quality affect household livelihood have estimated observable consumption- and labor-based household responses (Dewees, 1989; Heltberg *et al.*, 2000). Consumption-based measures have focused on estimating household firewood consumption, measured through either firewood expenditures or firewood collected, as a function of household, village, and environmental characteristics (Chen *et al.*, 2006), or in relation to household consumption of substitutes such as coal and kerosene (Pitt, 1985; Gupta and Köhlin, 2006; Gundimeda and Kohlin, 2008; Guta, 2014).[2] Labor-based outcome measures have focused on the effects of forest scarcity on who in the household collects firewood (men, women or children) and firewood collection time relative to other household activities such as agriculture. Most results indicate that scarcity measures (such as firewood price, firewood collection trip time and firewood distance) are not correlated with increased total collection time for specific household members (Amacher *et al.*, 1993; Cooke, 1998; Cooke *et al.*, 2000; Amacher *et al.*, 2004; Palmer and MacGregor, 2009).[3]

While these previous consumption- and labor-based studies are important, they do not enable one to estimate what a household would be willing to pay to maintain access to a forest resource. In other words, direct-use methods reveal behavioral responses but do not reveal welfare estimates. In a review of 12 different studies on the value of nontimber

[1]Based on FAOSTAT data, the annual deforestation rate in Africa from 2012 to 2016 was roughly 0.5 per cent per year, compared to a global rate of loss of 0.1 per cent. South America, the continent with the second-highest rate of deforestation, had a loss of only 0.2 per cent per year (Food and Agricultural Organization of the United Nations, 2017a).

[2]For a more complete, albeit somewhat dated, review of studies on firewood consumption, see Hyde *et al.* (2000).

[3]It is worth pointing out that four of the five studies cited here relied on less than 200 observations (Amacher *et al.*, 1993; Cooke, 1998; Cooke *et al.*, 2000; Palmer and MacGregor, 2009) so their power to detect a significant change was low. For a complete review of these studies, see Cooke *et al.* (2008).

forest products, Ferraro *et al.* (2012) found that only two of the 12 studies cited provided welfare estimates. In the same review, the authors note that the existing ecosystem service valuation studies generally rely on less rigorous valuation techniques; and, even rigorous valuation studies generally rely on cross-sectional data, which means that even these more rigorous estimates are prone to bias because of their inability to control for unobserved household characteristics.

In this paper, a unique household panel data set from Kagera, Tanzaniawas used to estimate a household's willingness-to-pay (WTP) for forest access. Specifically, the research focused on the use of forests for firewood collection and, like Pattanayak *et al.* (2004), applied the travel cost model to the case of firewood collection. First and foremost, this paper is a methodological paper. The primary goal was to understand how methodological decisions affect the resulting welfare estimates, with the aim of providing insight into how existing welfare estimates are affected by the estimation model, data used, or variable construction. In total, household WTP estimates for forest access under eight different estimation models were compared, and ten total models were estimated. Below, the two most important comparisons made in this paper are described in more detail.

First, household WTP estimates were compared under the assumption of perfect labor markets and constrained labor markets. If household members cannot freely choose how many hours they work outside of the home, then local wage rates do not represent their true opportunity costs of time. This comparison extends the travel cost model employed by Pattanayak *et al.* (2004) where local wage rates were used to construct households' travel costs. Instead, households' shadow wages were derived from estimates of a household profit function (Jacoby, 1993; Baland *et al.*, 2010). A household-specific travel cost index was then constructed that accounts for intra-household differences in shadow wages and firewood collection participation levels. WTP estimates were compared from this travel cost construction to a travel cost construction using village-reported wage data to assess how labor market assumptions affect welfare estimates.

Second, household WTP estimates were compared using a fixed-effects approach that controls for unobserved household characteristics to household WTP estimates using a cross-sectional approach. To the best of our knowledge, this paper is one of the first to investigate how WTP estimates are affected by the inclusion of household fixed effects. Given the relative scarcity of household panel data on firewood collection, it is important to understand how existing WTP estimates may or may not be biased given their inability to control for unobserved household characteristics. As alluded to above, previous research on this topic has relied almost exclusively on cross-sectional data (Pattanayak *et al.*, 2004; Baland *et al.*, 2010; Ferraro *et al.*, 2012).

In addition to providing a methodological comparison, this paper provides another data point on the potential magnitude of welfare estimates in relation to firewood collection, particularly in Sub-Saharan Africa where there is a limited body of research on the topic. Murphy *et al.* (2018) reviewed studies estimating fuelwood elasticity in developing countries and found that only two of the eight identified studies were done in Sub-Saharan Africa, with the majority of studies taking place in South Asia. Going forward, it is important to understand how forest access and welfare estimation may differ across regions.

It was estimated that, under the initial assumption of constrained labor markets, households in the Kagera region of Tanzania are willing-to-pay, on average \$120 per year (2016 USD) for access to local forests.[4] These WTP estimates were most sensitive to the inclusion of household fixed effects. Household WTP was estimated to be nearly 50 per cent higher when household fixed effects are not included in the estimation. WTP estimates were also sensitive to assumptions regarding the state of the local labor market; WTP estimates under the assumption of perfect labor markets were over 10 per cent higher than under the assumption of constrained labor markets. In contrast, WTP estimates were far less sensitive to the estimation model.

This paper proceeds as follows. Section 2 presents the estimation strategy for this analysis, focusing on the case of constrained labor markets. Section 3 describes the data source used in this study, the Kagera Health and Development Survey. Section 4 begins by presenting the estimation results for the case of perfect and constrained labor markets. It then presents the results of the eight additional estimation models and, when possible, compares the resulting WTP estimates across each of the estimated models. Finally, concluding remarks are provided in section 5.

2. Estimation strategy

In this section, an approach is developed develop to estimate household demand for firewood collection trips where household wages, earned from both marketed labor and household agricultural production, are adjusted for constrained labor markets.

In traditional single-site travel cost demand models, household demand for an environmental site is a function of the total number of trips taken to the site, household consumption of other goods and household income. In this case, the single site travel cost model was adapted to allow trips to the forest to be an input into a household firewood production process, an approach similar to that of Pattanayak *et al.* (2004) and Baland *et al.* (2010). However, in this paper, these earlier models were extended by allowing for multiple types of household workers, each with different preferences for leisure and work, and by allowing for constrained labor markets.

In the simplest case, when labor markets are perfectly functioning, household members are indifferent between hiring labor, providing labor at home and working in the market. For village v at time t the estimation of individual of type i in household k's demand for local forests, y, is relatively straightforward, because the market wage for individual i reflects their marginal productivity of labor:

$$y^*_{ik} = f(\beta_i(w_{ikvt}t_{ikvt}), \quad \beta_j(w_{jkvt}t_{jkvt}), \boldsymbol{\beta}_\theta \boldsymbol{\theta}_{kvt}, \boldsymbol{\beta}_\delta \boldsymbol{\delta}_{vt}, \eta_{kv}, \varepsilon_{ikvt}), \tag{1}$$

where w_{ivkt} reflects the market wage rate for individual i and t_{ikvt} reflects the time per firewood collection trip for individual i.[5] The vector $\boldsymbol{\theta}$ captures time-variant household characteristics, the vector $\boldsymbol{\delta}$ captures time-variant village characteristics, the term η_{kv} represents unobservable time-invariant household characteristics, and the term ε_{ikvt} is an independent and identically distributed error term.

As with other demand models, one expects the coefficient on β_i to be negative: as the cost of traveling to the forest increases for household member i, she should make fewer trips. Conversely, one expects the coefficient on β_j to be positive: as household member j's travel cost increases, household member i will make more trips.

[4]The correct welfare measure is compensating variation but this paper relies on the results in Willig (1976) and uses WTP as a proxy for compensating variation.

[5]Note that the estimated equation has two distinct types of household members, i and j, but the equation could easily be modified to include many more types.

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Equation (1) represents individual i in household k's demand for firewood collection trips. Household k's WTP for forest access is derived from aggregating the individual household members' demand for firewood trips.[6] This aggregate model is a function of a single travel cost variable, $w_{kvt}t_{kvt}$, created by using a price index that weights household members' travel costs by the share of total household firewood collection trips each member makes. Household WTP for forest access is measured as the area under this demand curve (Bockstael *et al.*, 1990).

If labor markets are not perfectly functioning, such as in the presence of transaction costs that prevent household members from working outside the home, then household production and consumption decisions are no longer separable (Jacoby, 1993). In this case, the household member that cannot work outside the home, say type j, has a shadow wage, $\hat{w}_j$, that is equivalent to the price of leisure. Empirically, constrained labor markets means that both shadow wages and household profit are choice variables and endogenous to the estimation process. Travel cost estimates from this case, however, better reflect unobserved constraints in many local labor markets; the separability of household consumption and agricultural production has been rejected by a number of studies (see Jacoby, 1993; Grimard, 1997; Le, 2010).

In the case of constrained labor markets, a two-step estimation approach is required. First, household members' shadow wages are estimated using a household profit function. Second, these estimated shadow wages are used as the wage variables in the travel cost estimation depicted in equation (1).

2.1. Estimating shadow wages

Household-specific shadow wages were derived from their corresponding labor hour coefficients in a household profit function (Jacoby, 1993; Baland *et al.*, 2010). Household profits are equal to the sum of profits from agriculture and non-farm self-employment and are assumed to follow a Cobb-Douglas functional form:[7]

$$\begin{aligned}\ln \text{profit}_{kvt} = {} & \alpha_0 + \alpha_1 \ln \text{land}_{kvt} + \alpha_2 \ln \text{livestock}_{kvt} \\ & + \alpha_3 \ln hh \text{ education}_{kvt} + \alpha_4 \ln \text{business}_{kvt} \\ & + \alpha_5 \ln \text{variable inputs}_{kvt} + \sum_j \phi_j \ln j \text{ labor}_{kvt} + \mu_{kv} + \epsilon_{kvt}. \qquad (2)\end{aligned}$$

Land, livestock, business and household education represent household k in village v's fixed assets at time t, measured as number of acres of land cultivation, value of household-owned livestock, value of non-farm business assets and average years of education for adults 15 years and older, respectively. Variable inputs include the total cost of purchased inputs for crop production (e.g., land, seed, hired labor, fertilizer, pesticide, transportation, and processing costs). The error term μ_{kv} denotes unobservable time-invariant household characteristics that are correlated with household labor hours

[6] Individual demand for firewood collection can be aggregated to the household level as long as household members' observed wages and shadow wages are positively correlated. In this case, Lewbel's generalization of Hicks' composite commodity theorem applies to household members' firewood collection trips (Hicks, 1946; Lewbel, 1996).

[7] A log transformation was used on all outcome and explanatory variables in the shadow wage estimates. All observations, except for adult male and adult female labor hours, were replaced with one if they are equal to zero.

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and ϵ_{kvt} is a serially independent, identically distributed error term that is assumed to be uncorrelated with all regressors.

While the Cobb-Douglas functional form is advantageous because of its intuitive interpretation, it requires that the marginal rates of transformation between any two household members be independent of all other inputs (Jacoby, 1993). This assumption was relaxed and a translog profit function was estimated that included squared labor terms and interaction terms between different household member's labor hours. Household fixed effects were included in both the Cobb-Douglas and translog estimations to control for unobserved household managerial ability.

For the case of the Cobb-Douglas functional form, the estimated coefficient ϕ_j from (2) is interpreted as the elasticity of household profit with respect to j's labor. Thus, to back out the shadow wage, the estimated coefficient, ϕ_j, was multiplied by the ratio of household k's profit to type j's labor hours at time t.[8]

2.2. Estimating household demand for firewood collection trips

Finally, equation (1) was estimated using the Poisson count model, which accounts for the discrete non-negative nature of firewood collection trip values. Again, household fixed effects were included to control for unobserved household characteristics (Haab and McConnell, 2002).[9] The Poisson fixed effects model was preferred to its primary alternative model, the negative binomial count model, because the Poisson model is consistent under much weaker distributional assumptions (Cameron and Trivedi, 2005). Consistency of the coefficient estimates with the Poisson model requires only that the conditional mean, given by:

$$\begin{aligned} \mathrm{E}[y_{kvt} \mid \boldsymbol{x}_{kvt}, \eta_k] = \eta_k \exp(&\beta_1 \text{ travel cost}_{kvt} + \beta_2 \text{ income}_{kvt} \\ &+ \boldsymbol{\beta}_p \textbf{ prices}_{vt} + \boldsymbol{\beta}_h \, \boldsymbol{hh} \textbf{ characteristics}_{kvt} \\ &+ \beta_3 \text{ bike}_{kvt} + \beta_4 \text{ car}_{kvt} + \beta_5 \text{ motorcycle}_{kvt}), \end{aligned} \tag{3}$$

be correctly specified.[10] In the estimation, observed household expenditures were a proxy indicator of household income, which has been shown to be strongly correlated with household income and to suffer less from measurement error.[11] In addition, the

[8]More specifically, for the case of the Cobb-Douglas production function, the shadow wage estimates are equivalent to $\hat{w}_j = \hat{\phi}_j \times \widehat{\text{profit}}/L_j^a$ where $\hat{\phi}_j$ is the estimated coefficient on group j's annual labor hours variable.

[9]For a Poisson model with household fixed effects, the probability that household k in village v at time t takes y_{kvt} firewood collection trips is:

$$\Pr[Y = y_{kvt} \mid \boldsymbol{x}_{kvt}, \boldsymbol{\beta}, \eta_k] = \frac{\exp(-\eta_k \lambda_{kvt})(\eta_k \lambda_{kvt})^{y_{kvt}}}{y_{kvt}!},$$

where $\lambda_{kvt} = \exp(\boldsymbol{x}'_{kvt}\boldsymbol{\beta} + \varepsilon_{kvt})$.

[10]This conditional mean requirement contrasts with the conditional mean requirement in the negative binomial model:

$$\mathrm{E}[y_{kvt} \mid \boldsymbol{x}_{kvt}, \eta_k] = \frac{\eta_k \exp(\boldsymbol{x}'_{kvt}\boldsymbol{\beta})}{\phi_{kv}}$$

where ϕ_{kv} represents the overdispersion parameter. If the overdispersion parameter is misspecified, then estimates from the fixed effects negative binomial model will be inconsistent (Cameron and Trivedi, 1998).

[11]Household expenditures include food expenditures, consumption of home production, non-food consumption expenditure, remittances sent, and wage income in kind (Ainsworth, 2004). Household income

prices vector includes the price of kerosene, price of charcoal and a food price index; and the ***hh*** **characteristics** vector includes a dummy equal to one if the household head is female, average years of education for adults 15 years and older, and the number of household members with restricted activity. Finally, three ownership dummies were included, indicating whether or not a household owned a bicycle, car or motorcycle.

Conditional maximum likelihood was used to obtain estimates of $\boldsymbol{\beta}$ (conditional on household-specific totals, $T\bar{y}_{kv} = \sum_{t=1}^{T} y_{kvt}$). Estimates for the perfect labor market scenario are displayed with clustered standard errors at the village level to account for heteroskedasticity in the error term. Estimates for the constrained labor market scenario are displayed with block-bootstrapped standard errors where standard errors were block-bootstrapped (500 replications) over both the first-stage shadow wage estimates and the second-stage demand estimates.

The value of forest access to households was measured as the area of the demand curve of households' demand for trips to the forest, or the consumer surplus (i.e., willingness-to-pay) for forest trips. In the case of equation (3), WTP per firewood collection trip was calculated as $-1/\hat{\beta}_1$ (Yen and Adamowicz, 1993).

In addition to estimating mean WTP, the 95 per cent confidence interval for each WTP estimate was also estimated. Estimating the confidence interval is important for understanding the possible range of the average WTP. But, because the estimated WTP is a function of the estimated coefficient for β_1, the WTP is also a random variable and the resulting standard error is not directly observed from the regression estimates. In practice, the distribution of the estimated mean WTP is rarely reported. Rosenberger (2016) recently reviewed 833 WTP estimates from 172 different papers using individual travel cost models. Of these 833 WTP estimates, only five per cent had reported standard errors and only 16 per cent had reported confidence intervals. Following Creel and Loomis (1991) and Yen and Adamowicz (1993), a Monte Carlo simulation that relied on the asymptotic normality of the coefficient estimates was used, under the assumption that the estimation model is the true model. Fifty thousand draws were made from the multivariate normal distribution with a mean vector given by the coefficient estimates and a covariance matrix given by the estimated covariance matrix. The 95 per cent confidence interval was then estimated as the 5th and 95th percentile values of the WTP estimates from the 50,000 draws. With this Monte Carlo simulation, the estimated confidence intervals are accurate even if the distribution of $\hat{\beta}_1$ is asymmetric.

3. Data

To illustrate the application of this model, data is used from the Kagera Health and Development Survey (KHDS), a regionally representative longitudinal household survey collected between 1991 and 1994 (The World Bank, 1991–1994). This survey is advantageous for a number of reasons. First and foremost, it is a longitudinal survey that contains information on the amount of time each household member spent collecting firewood across four consecutive years. Second, the survey contains a detailed firewood collection trip question; it asks each household member about the firewood collection trips she or he made over the last seven days. More recent longitudinal household surveys in Tanzania, such as the National Panel Survey (NPS) that was collected in 2008–2009, 2010, 2012–2013 and 2014–2015, collected information on firewood collection trips made only

data, especially data on household business income, may have a large amount of measurement error (Deaton, 1997).

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over the previous day. This more limited question is likely to underestimate the amount of time households spend collecting firewood as households that normally collect firewood but that did not collect firewood the previous day are recorded with zeros. In the 2008–2009 NPS, for example, over 70 per cent of households reported firewood as a major source of cooking fuel but only 42 per cent of these households reported making a firewood collection trip the previous day. In contrast, in the fourth survey round of the KHDS, over 95 per cent of households reported firewood as a major source of cooking fuel and over 90 per cent of these households reported making firewood collection trips in the previous week (see online appendix table A1).

The four survey rounds of the KHDS data used in this paper – despite being over 20 year old – remain one of the few surveys that provide detailed data on a household's firewood collection patterns over multiple years. For example, the subsequent rounds of the KHDS survey, collected in 2004 and 2010, combined firewood and water collection trips into a single question or omitted firewood collection trips altogether, respectively. And, as noted above, the firewood collection survey question in the four rounds of the NPS provided little variability in firewood collection trips across households. Thus, these data sets either prohibit the use of the travel cost model application altogether or prohibit the inclusion of household fixed effects. In this paper, it is argued that both of these components are necessary for more accurate estimates of household welfare related to nontimber forest products.

The KHDS surveyed over 800 households in the Kagera Region of Tanzania four times between September 1991 and January 1994.[12] The Kagera region (40,838 km^2) lies in the northwest corner of Tanzania on the western shore of Lake Victoria and borders Uganda, Rwanda and Burundi (see figure A1 in the online appendix). This study uses an unbalanced panel with 3,375 observations (840 in round 1, 849 in round 2, 858 in round 3, and 828 in round 4). The household attrition rate is low: between the 1991 and 1994 survey rounds the annual household attrition rate was 0.88 per cent and only 0.70 per cent after excluding deaths (Outes-Leon and Dercon, 2008, table 2: 4.). Survey rounds were conducted six to seven months apart and households were surveyed from 50 different villages across all five districts of Kagera. The KHDS used a two-stage stratified random sample; communities were stratified based on agroclimatic zone and adult mortality rates. The KHDS questionnaires were adapted from the World Bank's Living Standard Measurement Study surveys, with questionnaires administered to households, communities, local markets, local medical centers and local schools.

In the KHDS, all household members seven years and older were asked 'How many hours did you spend collecting firewood in the last seven days?' Responses to this question were used to construct a measure of the number of firewood collection trips made by each individual in the last week and a measure of the average time per trip across all household members. The number of weekly individual collection trips was approximated as the number of days that a household member reported a non-zero collection time.[13] An individual's trip time was measured as the total number of hours that she or he spent collecting firewood in the previous week divided by the number of trips she or he made.

[12] A household was defined as 'a person or group of persons who live in the same dwelling and eat together for at least three of the twelve months preceding the date of the survey' (Ainsworth, 2004).

[13] This trip frequency is accurate under the assumption that a household member is not making more than one firewood collection trip on any given day.

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The number of household firewood collection trips in the previous week is used as a proxy variable for a household's annual number of firewood collection trips. Less than five per cent of households store firewood (see table A1, online appendix), mostly because firewood collection is done by hand, so a significant amount of time would be required for a household to build up a firewood stock. As expected, the median number of weekly firewood collection trips varies little across the 12 months, providing evidence that seasonality is not a major factor in household firewood collection decisions (see figure A2 in the online appendix).

A household travel cost index was created by indexing adult male, adult female, teenager and child travel costs. Adults were categorized as individuals 16 years or older, teenagers were 12 to 15 years, and children were seven to 11 years. The travel cost index for household k in village v at time t is:

$$(\bar{w}t^f)_{kvt} = \sum_{\substack{j\,=\text{male, female,}\\ \text{teen, child}}} \frac{y_{jkvt}}{\sum_{\substack{i\,=\text{male, female,}\\ \text{teen, child}}} y_{ikvt}} (w_{jkvt} \times t^f_{kvt}). \tag{4}$$

The weights used in this index vary across households and are potentially correlated with unobservable household characteristics. This paper compares the resulting WTP estimates of using a fixed-effects estimation strategy to remove bias resulting from the correlation between a household's indexed travel cost and time-invariant unobservable household characteristics to WTP estimates when household fixed effects are excluded.

In the case of perfectly functioning labor markets, a household member's observed wage can be used to measure his or her opportunity cost of time. In this scenario, each community leader was asked a survey question about how much an agricultural laborer earns for a day's work and this answer was used. This question was asked separately for men, women and children.[14] In the case of constrained labor markets, however, the observed wage does not accurately measure a household member's opportunity cost of time. Instead, shadow wages were estimated as the marginal product of labor, as proposed by Jacoby (1993) and discussed in section 2.

For the analysis in this paper, households that report any firewood sales in the last six months (38 observations) were dropped. These households were assumed to use local forests for commercial purposes and not for private non-market use. Assuming that households selling firewood have a more inelastic own-price demand for firewood collection trips, the exclusion of these observations would result in the estimated travel cost coefficient being smaller in magnitude than if these observations were included. Second, also dropped were households reporting zero household expenditures (one observation), households with negative reported income (37 observations) and households with missing education information (three observations). Finally, in order to run the fixed-effects model, households were dropped with only one observation across the four survey rounds (40 observations) and households that reported no firewood collection trips across all four survey rounds (99 observations). In total, 217 observations were dropped, resulting in a final sample of 3,158 observations across the four survey rounds.

[14] Villages with missing reported wage data were given a wage equal to the sample mean for the relevant survey round. In some survey rounds, as many as 35 of the 50 villages have missing child wages.

4. Estimation results

In this section, estimation results are presented for firewood collection trips as a function of a household's travel cost per firewood collection. First household demand for firewood collection trips is estimated under the assumption of perfect labor markets and constrained labor markets using household fixed effects to control for all time-invariant unobserved household characteristics. Then, in the next sub-section, the sensitivity of these results is compared to a variety of different estimation specifications and travel cost constructions.

Table 1 displays summary statistics for the sample of interest. All prices and monetary variables are in real terms with round one as the base year; these variables are deflated using a Laspeyre's price index that is measured at the village level. Table 1 shows that, on average, households made between six and seven firewood collection trips each week across the four survey rounds; both adult females and adult males reported working, on average, over 1,000 hours annually on a home business or agriculture; and households typically had a little more than five members, had males as the household head, and had an average household education per member 15 years and older of slightly less than five years.

Household profit estimates are reported in table 2. Columns (1) and (2) report results from the Cobb-Douglas profit function presented in equation (2). In column (1), both male and female annual labor hours have a positive and significant effect on household profit, teenage annual labor has a positive but insignificant effect on household profit, and child annual labor has a negative and significant effect on household profit. A Wald Test fails to reject the null hypothesis that the elasticity of male and female labor hours are equal in column (1) (p-value of 0.824), but another Wald test rejects the null hypothesis that the elasticity of teenage and child labor hours are equal at the five per cent level (p-value of 0.034). Column (2) shows the results for the Cobb-Dougle profit function with a single coefficient for adult labor hours. Annual adult labor hours has a positive and significant effect on household profit in column (2) and teenage annual labor hours and child annual labor hours have similar effects to those reported in column (1). Finally, column (3) reports the results using a trans-log profit function. In the trans-log estimation, squared terms were included for all fixed and variable assets, for adult annual labor hours, and an interaction term for adult annual labor hours with child annual labor hours and teenage annual labor hours. All annual labor hour coefficients are significant in column (3).

The coefficient estimates on adult, teenage, and child labor hours are used to estimate group-level shadow wages (the sample mean shadow wage estimates are reported at the bottom of table 2). The translog profit function allows for more flexible labor decisions across household members and offers the best predictive power of all three estimates, as shown by the higher R^2 value reported at the bottom of table 2. The translog profit function may produce negative shadow wage estimates if there is surplus labor within a household (Sen, 1966).[15] However, only three observations were estimated to have negative shadow wages for adults and 288 observations were estimated to have negative shadow wages for teenagers. For children, 830 observations were estimated to have negative shadow wages, suggesting that households in the sample experienced surplus labor with regard to children's labor. In addition, nearly 3,000 observations reported

[15]Sen (1966) defines surplus labor as labor that can be removed from, in this case, agricultural production without reducing household profits.

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Table 1. Sample summary statistics

	Survey round				
	1	2	3	4	Total
Household profit (log)[a]	11.99 (1.34)	10.99 (1.15)	10.83 (1.06)	10.63 (1.27)	11.10 (1.31)
Household expenditure (log)[a]	12.51 (0.76)	11.63 (0.79)	11.58 (0.76)	11.52 (0.76)	11.80 (0.86)
Acres of cultivated land	3.95 (4.10)	3.90 (3.86)	3.96 (3.67)	4.35 (6.81)	4.04 (4.77)
Value of livestock (log)[a]	5.98 (4.56)	6.37 (4.42)	6.07 (4.49)	6.25 (4.34)	6.17 (4.45)
Value of variable inputs (log)[a]	9.21 (2.33)	8.37 (1.88)	7.72 (2.00)	7.26 (2.52)	8.13 (2.31)
Business assets (log)[a]	1.88 (3.72)	2.34 (3.93)	2.66 (3.93)	2.53 (3.99)	2.36 (3.90)
Adult male annual labor hours	1434.68 (1985.60)	1118.35 (1420.44)	1041.92 (1222.49)	978.82 (1149.93)	1141.41 (1486.24)
Adult female annual labor hours	1591.18 (1657.04)	1194.89 (1181.40)	1231.26 (1321.54)	1154.14 (1058.32)	1290.39 (1331.69)
Teenage annual labor hours	425.90 (820.26)	387.37 (744.57)	410.37 (731.32)	345.57 (584.21)	392.32 (725.40)
Child annual labor hours	149.01 (383.84)	169.05 (426.67)	207.90 (452.05)	172.45 (410.73)	174.92 (419.89)
Household firewood collection trips	7.22 (6.23)	6.33 (5.84)	5.83 (5.38)	6.41 (5.41)	6.44 (5.74)
Price of kerosene[a]	80.39 (15.83)	75.56 (15.57)	82.12 (17.38)	102.62 (22.45)	85.05 (20.74)
Price of charcoal[a]	0.06 (0.01)	0.04 (0.01)	0.04 (0.01)	0.05 (0.01)	0.05 (0.01)
Food price index[a]	0.20 (0.12)	0.17 (0.12)	0.14 (0.12)	0.11 (0.12)	0.16 (0.12)
Household size	5.96 (3.07)	5.78 (3.00)	5.77 (3.13)	5.71 (3.24)	5.80 (3.11)
Dummy if household head is female	0.26 (0.44)	0.27 (0.44)	0.28 (0.45)	0.27 (0.44)	0.27 (0.44)
Average household education (years)	4.36 (2.72)	4.46 (2.80)	4.49 (2.72)	4.48 (2.97)	4.45 (2.80)
Observations	767	810	805	776	3158

Note: Standard deviation in parentheses.
[a] Values normalized to 1991 Tanzanian shillings.

child-labor hours of zero. Thus, it was assumed that children are at a corner solution in the labor market and, consequently, their wages were assigned to be one.

A household's travel cost was then constructed under the two possible labor market scenarios: perfect labor markets and constrained labor markets. Under the assumption of perfect labor markets, the observed sample wage was used to construct a household's

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Table 2. Household profit: ordinary least squares with fixed effects
Dependent variable: log of profit from self-employment (business and agriculture)

	Cobb-Douglas		Translog
	(1)	(2)	(3)
Adult male annual labor hours (log)	0.018* (0.009)		
Adult female annual labor hours (log)	0.022** (0.011)		
Adult annual labor hours (log)		0.047*** (0.012)	−0.099* (0.049)
Teenage annual labor hours (log)	0.001 (0.009)	0.000 (0.009)	−0.058** (0.025)
Child annual labor hours (log)	−0.027*** (0.008)	−0.027*** (0.008)	0.055** (0.027)
Adult labor^2 (log)			0.017*** (0.006)
Adult labor × Child labor			−0.010*** (0.004)
Adult labor × Teenage labor			0.008** (0.004)
Observations	3,158	3,158	3,158
R^2 within	0.180	0.182	0.261
p-value for Wald test $\hat{\alpha}_f = \hat{\alpha}_m$	0.824		
p-value for Wald test $\hat{\alpha}_c = \hat{\alpha}_t$	0.034	0.038	
Adult male shadow wage^a	3.022		
Adult female shadow wage^a	3.024		
Adult shadow wage^a		3.938	10.351
Teenage shadow wage^a	0.398	0.092	3.230

Note: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the village level (in parentheses).
Note: All estimates include additional household- and village-level controls (coefficients not reported): land areas, value of livestock, value of business assets, value of variable inputs, and a dummy for interview month. The trans-log regression includes squared terms for land area, value of livestock, value of business assets, and value of variable inputs as well. A one is added to reported zeros for all explanatory variables.
^{a}Shadow wages are calculated as $\hat{w}_j = \partial \mathrm{E}[\ln \text{profit}]/\partial \ln L_j^a \times \widehat{\text{profit}}/L_j^a$ for j=m,f,t. Sample means reported over households that have an estimated shadow wage that is positive and non-zero labor hours. Child shadow wages are omitted because they are estimated to be negative in columns (1) and (2) and only 31 households have positive child shadow wages in column (3).

travel cost and, under the assumption of constrained labor markets, a household's estimated shadow wage, as reported in column (3) of table 2, was used to construct the household's travel cost. Table 3 reports the summary statistics for community wage rates (sample wage), shadow wages, and all other variables used in the construction of the indexed household-level travel cost. The weight variables indicate that adults make the largest proportion of firewood collection trips.[16] Finally, travel cost estimates differ

[16]Adult males make the largest proportion of firewood collection trips in rounds one and two, while there is no significant difference in the proportion of trips made by adult males and adult females in rounds three and four.

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Table 3. Travel cost summary statistics using reported and estimated wages

	Survey round				
	1	2	3	4	Total
Adult male weight	0.36 (0.42)	0.37 (0.42)	0.33 (0.41)	0.31 (0.40)	0.34 (0.41)
Adult female weight	0.29 (0.38)	0.28 (0.38)	0.28 (0.39)	0.29 (0.39)	0.29 (0.38)
Child weight	0.10 (0.22)	0.11 (0.22)	0.13 (0.24)	0.12 (0.25)	0.11 (0.23)
Teenage weight	0.21 (0.31)	0.21 (0.31)	0.21 (0.31)	0.22 (0.32)	0.21 (0.31)
Travel time (hours)	1.75 (1.17)	1.59 (1.13)	1.47 (0.95)	1.37 (0.96)	1.55 (1.06)
Observations (collecting households)	726	742	725	689	2882
Adult shadow wage[a]	15.75 (12.60)	10.40 (9.73)	10.56 (8.68)	8.23 (6.95)	11.21 (10.07)
Adult sample wage[b]	17.93 (5.77)	20.20 (6.62)	22.27 (8.34)	23.20 (8.43)	20.91 (7.65)
Teenage shadow wage[a]	7.71 (7.40)	3.67 (4.19)	3.79 (4.46)	2.97 (3.74)	4.51 (5.45)
Teenage sample wage[b]	13.63 (3.81)	19.35 (5.30)	15.20 (4.77)	21.13 (9.20)	17.34 (6.81)
Travel cost (shadow wage)[c]	20.50 (27.80)	12.11 (16.67)	10.56 (13.20)	8.29 (11.72)	12.81 (18.91)
Travel cost (sample wage)[c]	27.22 (22.49)	32.13 (28.78)	28.72 (26.49)	32.60 (37.22)	30.19 (29.31)
Observations (all households)	767	810	805	776	3158

Note: Standard deviation in parentheses. Values normalized with round 1 as base prices.
[a]Three adjustments are made for the full-sample estimation of shadow wages: (i) to reduce the effect of outliers, a household's estimated shadow wages for adults and teenagers are capped at the 99th percentile for that respective variable across all survey rounds (29 adult shadow wages and 14 teenage shadow wages); (ii) households with zero reported adult or teen labor hours in a given round are assigned their village maximum shadow wage for that round (192 adult shadow wages and 1,653 teenage shadow wages); (iii) households with negative estimated adult or teen shadow wages in a given round are assigned their village minimum (non-negative) shadow wage for that round (3 adult shadow wages and 288 teenage shadow wages).
[b]Villages with missing reported wage data are given a wage equal to the sample mean for the relevant survey round.
[c]Households with no firewood collection trips in a given round are assigned their village maximum travel cost for that round (276 observations).

depending on the method of wage measurement used; estimates based on the sample average wage are, on average, higher than travel cost estimates based on the shadow wage.

In the construction of a household's travel cost, four adjustments were made to the estimated values. First, the impact of outliers was removed by capping a household's estimated adult or teenage shadow wage at the 99th percentile of estimated adult or teenage shadow wages, respectively, across all four survey rounds. This adjustment will tend to reduce the magnitude of the estimated travel cost coefficient. Second, households where adults or teenagers do not participate in agriculture or a home-business (e.g., households that report zero adult or teenage home labor hours) are assigned shadow wages for that

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group equal to the maximum village shadow wage for a given survey round. This imputation follows the approach taken by Murphy *et al.* (2018) and assumes that households that do not participate in a given activity do not participate because their cost of participation (e.g., foregone wages) exceeds the benefits of participation (e.g., shadow wages). Third, households with estimated negative adult or teenage shadow wages are assigned the village minimum non-zero adult or teenage shadow wages, respectively, for a given survey round. Lastly, households that do not participate in firewood collection in a given survey round are assigned their village maximum travel cost for that survey round.

These estimated travel costs were used to estimate the travel cost model presented in equation (3). Travel cost estimates are presented in table 4. The travel cost, household size, and household expenditure coefficients are significant in both regressions. Most notably, the sign on travel cost is negative, indicating that households in Kagera behave rationally in deciding how many firewood collection trips to make; an increase in household travel costs reduces the number of weekly firewood collection trips made by a household. Additionally, the coefficient on household expenditures is positive, indicating a positive firewood income elasticity. The coefficients on price of kerosene, price of charcoal and the food price index are insignificant in both regressions, indicating that households may not have a substitute for firewood.

Coefficient estimates can be interpreted as semi-elasticities. From the estimates in column (1), holding all else constant, a one-hour increase in travel time corresponds to, on average, a 21 per cent decrease in the weekly number of household firewood collection trips over the previous week. In column (2), a one-hour increase in travel time, holding all else constant, corresponds to, on average, a 23 per cent decrease in the weekly number of household firewood collection trips over the previous week. The Poisson fixed effects model does not allow for the estimation of the marginal effects of travel cost on weekly household firewood collection trips because the marginal effects of travel cost are a function of the unobserved household characteristics, η_{kv}.[17]

4.1. Sensitivity analysis

This sub-section looks at the sensitivity of the results to a change in the estimation specification, a change in the construction of a household's travel cost, and a change in the estimation sample. The aim of these sensitivity tests is to evaluate the effects of controlling for unobserved household characteristics, the effects of different constructions of households' travel costs, and the effects of different distributional assumptions on the estimated travel cost coefficient and corresponding WTP. The results of all of these additional estimations are shown in table 5.

First, the fixed effects travel cost model in column (2) of table 4 was estimated excluding household fixed effects. With these results, it is possible to evaluate the degree of bias that may occur when unobserved household characteristics are not controlled for within the estimation. The cross-sectional estimates include additional controls for whether a household lives in an urban area, survey round fixed effects and village fixed effects.

[17]For example, the marginal effects for travel costs, $(\bar{w}t^f)_{kvt}$, are given by:

$$ME_{(\bar{w}t^f)_{kvt}} = \frac{\partial \mathrm{E}[y_{kvt}]}{\partial (\bar{w}t^f)_{kvt}} = \eta_{kv} \exp(\boldsymbol{x}_{kvt}\boldsymbol{\beta})\beta_1$$

and η_{kv} is unobservable.

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Table 4. Household travel cost estimates: Poisson fixed effects
Dependent variable: weekly household fire collection trips

	Perfect labor markets (1)	Constrained labor markets (2)
Travel cost (sample wage)	−0.021*** (0.001)	
Travel cost (shadow wage)		−0.023*** (0.008)
Household expenditure (log)	0.124*** (0.036)	0.176*** (0.040)
Price of kerosene	0.006 (0.005)	0.005 (0.005)
Price of charcoal	−2.998*** (6.129)	−0.435*** (6.821)
Food price index	1.597 (2.018)	2.513 (2.237)
Household size	0.071*** (0.014)	0.066*** (0.014)
Household head (=1 if female)	−0.118 (0.114)	−0.125 (0.135)
Average household education	0.012 (0.010)	−0.000 (0.011)
Household members with restricted activity	−0.005 (0.018)	−0.011 (0.022)
Dummy if household owns bicycle	−0.082 (0.053)	−0.057 (0.062)
Dummy if household owns car	−0.154 (0.330)	−0.325 (0.693)
Dummy if household owns motorcycle	0.830*** (0.272)	1.005 (2.165)
Observations	3158	3158

Note: ***$p < 0.01$. Cluster robust standard errors in parentheses for the perfect labor market scenario. For constrained labor markets, standard errors are block-bootstrapped over both the first stage (household profit function) and second stage (travel cost) and are shown in parentheses.

Column (1) of table 5 lists the results from this estimation. When unobserved household characteristics are excluded from the analysis, the estimated coefficient on travel cost decreases in magnitude and the estimated coefficient on household expenditures decreases, although both remain significant at the one per cent level.

Next, two alternative estimates of a household's travel cost were constructed. First, demand for firewood collection trips was estimated under corner labor market solutions, where total household demand is not a function of any wage rate.[18] Estimates from the case of corner labor markets are straightforward, do not rely on any wage construction and travel cost coefficients are easily interpreted in terms of firewood collection travel

[18] At a corner solution household member $j = 1{,}2$ cannot work additional hours in the labor market for wage w_j and there are little or no productivity gains from working at home, i.e., $\hat{w}_j \approx 0$ (Bockstael *et al.*, 1987).

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Table 5. Household travel cost estimates: robustness checks
Dependent variable: weekly household firewood collection trips

	Poisson	Poisson FE			Negative binomial FE	OLS FE	Ordered multinomial	
	(1) Cross sectional[a]	(2) Corner Markets	(3) HH majority	(4) No wood crop	(5)	(6)	(7) Probit[a]	(8) Logit[a]
Travel cost (shadow wage)	−0.015*** (0.003)			−0.021*** (0.007)	−0.023*** (0.009)	−0.073*** (0.024)	−0.025*** (0.003)	−0.049*** (0.005)
Travel time (hours)		−0.457*** (0.020)						
Travel cost (HH majority)			−0.018*** (0.005)					
Household expenditure (log)	0.133*** (0.034)	0.182*** (0.034)	0.179*** (0.040)	0.142*** (0.047)	0.133*** (0.043)	0.916*** (0.265)	0.111*** (0.044)	0.169*** (0.083)
Observations	3158	3158	3158	2454	3158	3158	3158	3158

Note: ***$p < 0.01$. Standard errors in parentheses. Two stage block-bootstrap standard errors displayed for columns (1) through (6). Cluster robust standard errors displayed for columns (7) and (8). All estimates include the following additional controls: female household head, average household education, members with restricted activity, household owns bicycle, household owns car, household owns motorcycle, price of kerosene, price of charcoal, food price index and household size. Coefficients not reported.
[a]Columns (1), (7) and (8) include urban dummy, survey round fixed effects and village fixed effects. Coefficients not reported.

time. Column (2) of table 5 lists the results from the case of corner labor markets; they show that a one-hour increase in travel time corresponds to a 46 per cent decrease in the weekly number of household firewood collection trips.

Second, an estimate of a household's 'typical trip to collect firewood' was constructed, similar to the travel cost construction used by Pattanayak *et al.* (2004). In this travel cost construction, households were assigned the travel cost that corresponds to the household group (e.g., adults, teenagers or children) that reported making the largest share of firewood collection trips.[19] Estimation results for this construction are presented in column (3) of table 5. Travel cost estimates were smaller in magnitude when this travel cost measure was used relative to the weighted average travel cost.

Next, all households that reported having a firewood crop were dropped to test whether there is a differential impact of travel cost on firewood collection trips for households that have fewer firewood collection location choices (i.e., households with no firewood crop can only collect firewood on public land). These results are presented in column (4) of table 5. Travel cost coefficient estimates are smaller in magnitude compared to column (2) in table 4 because households without a firewood crop have no alternative firewood sources and are likely to be less responsive to travel costs.

Finally, in columns (5) through (8) of table 5, the original model was re-estimated, assuming different distributional and demand form assumptions. In column (5), a negative binomial count model with household fixed effects was estimated.[20] In columns (6) through (8), household demand for firewood collection trips was estimated as a linear function using both ordinary least squares (OLS) with household fixed effects and ordered multinomial choice models. The ordered probit and logit models allow weekly firewood collection trips to be a proxy for unobserved household use of forests and model firewood collection trips on an ordinal scale, as compared to the cardinal scale modeled with the count models (Cameron and Trivedi, 1986). The ordered probit and logit models are both run as cross-sectional estimates and include the same additional controls used in the cross-sectional model reported in column (1) of table 5. The coefficient on travel cost remains negative in all of the estimates, providing further evidence that households respond rationally to firewood collection travel costs and reduce the number of weekly firewood collection trips they make as their travel cost increases.

4.2. Community forest valuation

In this sub-section, the WTP estimates derived from the different travel cost estimations reported in tables 4 and 5 were calculated and compared. Table 6 summarizes the WTP estimates from each of the travel cost estimations. The WTP estimates from the case of corner markets (column (2) of table 5) were not calculated because the travel cost construction in that model was non-monetary. In addition, the WTP estimates for the two ordered multinomial models (columns (7) and (8) in table 5) were not calculated because the ordinal scale assumed within the models prevents comparable calculations.

[19] Note that 43.7 per cent of observations were assigned an adult's travel cost, 15.8 per cent of observations were assigned a teenager's travel cost and 8.4 per cent of observations were assigned a child's travel cost. Also, 10.7 per cent of observations had two groups make the largest share of firewood collection trips; these observations were randomly assigned one of the two group's travel costs.

[20] Because the Poisson fixed effects estimates are more robust to distributional assumptions, the negative binomial results may be inconsistent due to a misspecified variance.

Table 6. Summary of willingness-to-pay results

Travel cost construction (1)	Wage estimate (2)	Estimation model (3)	Estimation sample (4)	WTP per trip[a] (5)	WTP as multiple of annual forest expenditure (6)	WTP as share of household expenditure (7)	Elasticity of trips with respect to travel cost (8)
Weighted	Shadow wage	Poisson FE	All households	\$0.36 (\$0.23–\$0.86)	1.49 (0.94–3.54)	0.07 (0.05–0.17)	−0.30 (−0.12−−0.47)
Weighted	Sample wage	Poisson FE	All households	\$0.40 (\$0.37–\$0.44)	1.65 (1.52–1.81)	0.08 (0.07–0.09)	−0.63 (−0.57−−0.68)
Weighted	Shadow wage	Poisson	All households	\$0.54 (\$0.40–\$0.84)	2.23 (1.64–3.46)	0.11 (0.08–0.17)	−0.20 (−0.13−−0.27)
Majority collector	Shadow wage	Poisson FE	All households	\$0.47 (\$0.31–\$0.99)	1.95 (1.28–4.06)	0.09 (0.06–0.20)	−0.23 (−0.11−−0.36)
Weighted	Shadow wage	Poisson FE	HHs with no wood crop	\$0.40 (\$0.25–\$0.97)	1.71 (1.07–4.09)	0.08 (0.05–0.20)	−0.27 (−0.11−−0.42)
Weighted	Shadow wage	Negative binomial FE	All households	\$0.36 (\$0.22–\$0.87)	1.47 (0.92–3.56)	0.07 (0.04–0.17)	−0.30 (−0.12−−0.48)
Weighted	Shadow wage	OLS FE	All households	\$0.37 (\$0.24–\$0.80)	1.52 (0.97–3.32)	0.07 (0.05–0.16)	−0.93 (−0.43−−1.45)

Note: 95% confidence interval calculated using Monte Carlo simulation using 50,000 draws (in parentheses). WTP per trip for OLS FE regression evaluated at the sample mean number of weekly firewood collection trips.

[a]Statistic calculated as $-\hat{y}_{kvt}/\hat{\beta}_1$. Values reported in 2016 US dollars. To convert 1991 Tz shillings to 2016 US dollars, we first used the Tanzanian consumer price index from the World Bank's Global Financial Development data series, relying on the annual average consumer price index. We then converted 2016 Tz shillings to 2016 US dollars using the International Monetary Fund's International Financial Statistics data series, relying on the annual average exchange rate. After both of these steps, it was estimated that one Tz shilling in 1991 is worth roughly \$0.01 in 2016 US dollars.

From table 6, one can easily compare differences in the WTP estimates across the various travel cost estimations, thereby isolating the effects of different estimation strategies on WTP. The mean WTP estimate using the Poisson fixed-effects model with a household's weighted shadow wage travel cost is \$0.36 2016 USD compared to \$0.36 and \$0.37 using a negative binomial fixed-effects model and OLS fixed-effects model, respectively. This result suggests that the empirical model used may not ultimately have a large effect on the mean WTP estimate. In contrast, the WTP estimates in table 6 suggest that the construction of a household's travel cost can have a large impact on WTP estimates. A household's WTP per firewood collection trip is over 30 per cent higher when the shadow wage of the majority collector is used to construct the travel cost as opposed to the household's weighted travel cost, \$0.47 compared to \$0.36. In addition, the use of the village sample wage produces WTP estimates that are nearly 10 per cent higher and greatly reduces the variability in WTP estimates across households compared to the use of a household's shadow wage. The WTP estimates that rely on a household's shadow wage show that WTP estimates could be as high as \$0.86 per trip, over twice as high as the estimated average, compared to the WTP estimates that use the village average sample wage, which only range from \$0.37 to \$0.44. Finally, the WTP estimates in table 6 demonstrate the importance of controlling for unobserved household characteristics; average WTP estimates are nearly 50 per cent higher when household fixed effects are excluded from the estimation (\$0.54 per trip).

To put these WTP estimates in perspective, households' WTP for annual access to local forests were calculated by multiplying the per-trip WTP estimates by the mean number of household firewood collection trips.[21] For the case of constrained labor markets with a weighted travel cost, on average, households are willing to pay \$120.73 in 2016 US dollars with a 95 per cent confidence interval of US\$76.01 to US\$288.16.[22]

Next, households' WTP for annual access to local forests can be compared to household-reported values of firewood consumption and household expenditure. These results are shown as multiples in columns (6) and (7) of table 6. All households in the survey were asked to value the amount of firewood that they used over the last two weeks, including both purchased and collected firewood. These values were then aggregated to an annual number. For households that predominately collect firewood, which is the vast majority of the sample, it is expected that these two values would be equivalent. As shown in table 6, a household's WTP for annual forest access is consistently higher than a household's reported annual value of firewood consumption. This result is consistent across all estimation methods with a household's WTP for annual forest access generally being at least 50 per cent higher than a household's reported annual value of firewood consumption. These results suggest that households may have a strong tendency to undervalue the value of local forest access when asked directly.

Column (7) of table 6 shows that, on average, households' WTP for annual forest access is slightly less than 10 per cent of their annual household expenditures, with some of the confidence intervals ranging as high as 20 per cent. For comparison, US households spent, on average, three per cent of their annual household expenditures on natural gas and electricity in 2017; US households earning less than US\$15,000 annually

[21] Because the unobserved household fixed effect is not estimated, it was not possible to estimate annual WTP estimates using the predicted number of household collection trips.

[22] It is worth noting that the results presented in this paper are similar in scale to the annual WTP estimated by Pattanayak *et al.* (2004). In their paper, the authors estimated a mean per trip WTP of US\$0.55 and an annual WTP of US\$122 per household.

still spent only five per cent of their annual household expenditures on natural gas and electricity.[23]

Finally, column (8) of table 6 shows the estimated travel cost elasticity of household firewood collection trips.[24] For five of the seven estimation models, the average elasticity estimates range between −0.2 and −0.3. For the OLS model, however, the elasticity estimate is, on average, −0.93 with the confidence interval extending as far as −1.45. These results provide further evidence that firewood consumption in many rural areas is inelastic but also suggest that the elasticity estimates may be sensitive to the distributional assumptions made in the estimation.

5. Conclusions

This paper assesses the extent to which welfare estimates are impacted by the data used and/or decisions made regarding variable construction or estimation model. A reliable means of measuring the benefits that households derive from access to local natural resources is important, as efforts increase to scale conservation efforts, such as forest conservation as a means of carbon mitigation and biodiversity preservation. With reliable estimates of households' WTP for forest access, policy makers and conservationists alike can more accurately weigh the welfare tradeoffs of reducing forest access in a given region. However, too often the tendency is for studies to publish a single WTP estimate, ignoring the sensitivity of their estimate to modeling assumptions. In particular, it was found that WTP estimates may be most sensitive to unobserved household characteristics and assumptions regarding the local labor market.

There are three main caveats to this paper that merit attention. First, there was no direct measure of the relative firewood collection productivity across household members or of environmental quality. To the extent that either of these variables are not captured by the household fixed-effect, they may lead to biased coefficient estimates. The omission of forest quality, frequently measured as forest density, may bias travel cost estimates downward if an increase in forest density is associated with a decrease in travel time and an increase in the number of firewood collection trips. This downward bias on travel cost coefficient estimates means that the WTP benefits would be a lower bound on the true level of benefits. Future analyses would benefit from direct and reliable estimates of environmental quality and collection productivity for households over time.

Second, a regional travel cost model was estimated in which the dependent variable is the total number of household firewood collection trips independent of the site visited. Consequently, it was not possible to measure the benefits of any particular forest site or the effects of changing forest quality on the location of firewood collection trips. A more detailed multi-site travel cost estimation would allow for the analysis of different environmental quality characteristics on household firewood collection decisions and provide more information on which forest attributes households value most.

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[23] US household expenditure data for 2017 obtained from the Consumer Expenditure Survey as published by the Bureau of Labor Statistics.

[24] The coefficient on travel cost represents the semi-elasticity, or:

$$\mathrm{E}[y_{kvt}|\boldsymbol{x}_{kvt}]\,\frac{\partial \mathrm{E}[y_{kvt}|\boldsymbol{x}_{kvt}]}{\partial\ \text{travel cost}_{kvt}} = \beta_1.$$

Elasticity estimates were obtained by multiplying travel cost coefficient estimates by the average household travel cost.

Third, the estimations in this paper relied on data that were nearly three decades old. To the degree that household reliance on firewood collection for woodfuel has shifted dramatically since the early 1990s, the monetary WTP estimates presented here will no longer be reliable or applicable. As noted above, however, over 700 million women globally are engaged in woodfuel collection (Food and Agriculture Organization of the United Nations, 2017b) so progress made in how best to estimate the monetary value of these activities remains as relevant today as it was thirty years ago. Moreover, despite the older data used in this paper, the results support previous research showing that, in many developing countries, households' demand for firewood is inelastic and that households would be willing to spend a significant amount of their resources on forest access. In particular, these results provide additional evidence for this conclusion in Sub-Saharan Africa where, to date, there have been far fewer studies (Murphy *et al.*, 2018). In this study, households are willing to pay, on average, \$120 per year (2016 USD) for forest access, or roughly seven per cent of their annual household expenditures. Under all modeling assumptions, the WTP estimates were larger than households' reported values of firewood consumption, suggesting that traditional contingent valuation surveys, where households are directly asked how much they value forest access, may underestimate the true benefits of forest access in Sub-Saharan Africa.

Going forward, more work remains in capturing the value of non-market resources to households in developing countries and in incorporating these values into conservation programs. As payment for ecosystem service programs grow, it will be increasingly important to incorporate the correct payment level into these programs, both to ensure conservation wins are made and to ensure that these programs are as cost effective as possible. The scale of the impact of these knowledge gains is large; a recent review by Salzman *et al.* (2018) estimated that there are currently over 550 active payment for ecosystem service programs globally with over \$30 billion in annual transactions. Early evidence suggests that payment for ecosystem service programs can be a cost-effective means of carbon mitigation (Jayachandran *et al.*, 2017), but work remains in understanding how best to assign and structure payments.

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