# Spatial Patterns of Market Participation and Resource Extraction: Fuelwood Collection in Northern Uganda

Daniela A. Miteva, Randall A. Kramer, Zachary S. Brown, and Martin D. Smith

While distance to markets is a key determinant of market participation for households that are dependent on natural resources, the distance to the resource stock is also essential. Thus, a household's location with respect to markets and the resource stock determines household market participation and associated resource degradation. Applying a discrete-choice framework for fuelwood collection in a developing country, we characterize the spatial pattern of market participation regimes and forest use. All else being equal, autarkic households are closest to the forest and furthest from the market, buyer households are closest to the market and furthest from the forest, and seller households are at intermediate distances. Empirical tests based on survey data from northern Uganda support the predictions from our theoretical model. Our findings have important implications for understanding the spatial patterns of forest degradation and determining the control group when designing impact evaluations of the effectiveness of development and conservation interventions.

*Key words*: Spatial model, household sorting, household production, transaction costs, fuelwood extraction, deforestation, forest degradation, sub-Saharan Africa, quasi-experimental research designs.

*JEL codes*: O13, Q23, Q50.

Fuelwood collection is a primary source of household fuel and contributes to forest degradation and deforestation in developing countries (Bailis et al. 2015). While many empirical studies use spatially explicit data to evaluate the effects that conservation policies, roads, and other disturbances have on deforestation, only a fraction of these studies conduct rigorous causal inference, and still fewer analyze the mechanisms driving deforestation (Miteva, Pattanayak, and Ferraro 2012). In this article we focus on the mechanisms that influence fuelwood extraction, derive the resulting implications for spatial patterns of forest degradation, and test the predictions of the model with geocoded survey data.

To understand fuelwood collection, we model households sorting into different market participation regimes as a function of spatial attributes (proximity to forests and markets). Although models of choice regarding market participation regime are common in the agricultural and development applications (e.g., Amacher, Hyde, and Kanel 1996; Robinson, Williams, and Albers 2002; Sills et al. 2003;

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Ouma et al. 2010), no previous study has examined the spatial patterns of a market participation regime that arise due to differences in location. Using a discrete-choice framework, we predict a spatial pattern of household market participation regimes as follows: households close to the forest but away from the market are autarkic; households close to the market but away from the forest are buyers of fuelwood; and households in-between are sellers of fuelwood.

We follow the agricultural development literature in which market failures are household- rather than commodity-specific, with the household location and socio-economic characteristics being the determinants of household participation in the market (de Janvry, Fafchamps, and Sadoulet 1991; Key, Sadoulet, and de Janvry 2000; Robinson, Williams, and Albers 2002). Whether or not a household participates in the market as a buyer or a seller depends on the household's location with respect to the market and the transaction costs it incurs. The lack of infrastructure and limited information increase the transaction costs (de Janvry, Fafchamps, and Sadoulet 1991; Key, Sadoulet, and de Janvry 2000). Similarly, the household's decision of whether or not to produce a commodity such as fuelwood depends on the household's location relative to the forest and/or the forest quality at the site (e.g., Robinson, Williams, and Albers 2002; Pattanayak, Sills, and Kramer 2004; Schaafsma et al. 2012). If the distance to the forest is too great or the forest has been significantly degraded, it may be optimal for the household to purchase fuelwood from the market rather than to collect it. Combining these insights, we model the extractive behavior of a household as determined by both marginal transaction costs (e.g., search costs) associated with the forest quality (with a decreasing level of quality increasing the marginal cost of extraction), and fixed transaction costs associated with travelling to the market and the forest.[1]

We extend the static household production model in Key, Sadoulet, and de Janvry (2000) to fuelwood collection in a developing country, specifically postwar northern Uganda, where the natural environment was able to recover during the prolonged military conflict, but where now forests are being depleted at an alarming rate (Nampindo, Phillipps, and Plumptre 2005).[2] We add to previous studies considering transaction costs as determinants of household fuelwood collection behavior (e.g., Köhlin and Parks 2001; MacDonald, Adamowitz, and Luckert 2001; Robinson, Williams, and Albers 2002; Fafchamps and Hill 2004; Pattanayak, Sills, and Kramer 2004; Albers and Robinson 2013) by explicitly modeling the role of household-specific location with respect to both markets and forests in a discrete-choice framework. The presence of fixed transaction costs introduces discontinuities in the traditional household optimization model; the household has to choose the market participation regime that yields the highest utility and, conditional on that, how much fuelwood, if any, to produce. In other words, we consider fuelwood collection on both the intensive and extensive margins. We allow households to be scattered in space; whether and how much fuelwood a household collects is determined by the presence of both proportional and fixed transaction costs. Similar to MacDonald, Adamowitz, and Luckert (2001) and Robinson, Albers, and Williams (2008), we treat space as being comprised of discrete forest patches that may or may not be adjacent to each other.

We apply a flexible discrete-choice framework that allows us to combine spatial heterogeneity as proxied by distances to discrete markets and discrete forest patches that do not need to coincide with the household location and choices between market participation regimes. Thus, we attempt to integrate insights from the development and environmental economics literature (e.g., the two-stage optimization characteristic of sorting models). In this article we focus on understanding the role of location in household extractive decisions that affect poverty and the forest ecosystems in the area. Thus, our work

[1] The key difference between the two types of costs is whether or not they vary with the amount of fuelwood collected. An example of a fixed transaction cost is the cost of renting/buying a bicycle to travel to the market, or the cost of time to traverse a distance under the assumption that villagers do not vary their speed with the amount of fuelwood. The proportional transaction costs are associated with searching for fuelwood: the more degraded the forest is, the costlier in terms of effort and time it is to collect fuelwood. These costs depend on the amount of fuelwood collected.

[2] For example, our calculations using geospatial forest cover data at 300-meter resolution indicate a forest loss of 0.868% of the total area of Gulu and Oyam Districts from 2006 to 2009.

adds to the literature on understating household behavior and the impact that conservation and development policies have in forest-dependent communities.

Unlike previous models (e.g., Robinson, Williams, and Albers 2002; Robinson, Albers, and Williams 2008; Robinson and Lokina 2011), we use a unique spatially-explicit dataset to test the predictions of our model. Our data come from an area that experienced a nearly twenty-year military conflict and the displacement of almost the entire rural population (van Acker 2004). Households in our survey are returning to their homesteads after a lengthy war, during which the natural vegetation in the area was able to recover (Nampindo, Phillipps, and Plumptre 2005). As a result, household location with respect to forest cover is a source of exogenous variation for testing our model; the landscape sorts market participation spatially, but the households' location in the landscape is exogenous. We find statistically significant and robust spatial patterns in accordance with the predictions from our model: (*a*) buyers tend to be located close to markets and away from forest patches; (*b*) sellers are at intermediate distances between forests and markets; (*c*) autarkic households are located furthest from markets and to cities. Our empirical approach builds upon previous work on fuelwood collection by combining heterogeneity in the household characteristics (and the opportunity costs of labor) with spatial heterogeneity in terms of varying distances to discrete forest patches and markets. We use spatially-explicit household data from an area with high poverty levels and high dependence on natural resources to provide empirical support for the predictions of our models. We demonstrate that, after conditioning on household characteristics, features of the landscape sort households spatially into market participation regimes, as our theoretical model predicts.

## A Two-Stage Model of Household Market Participation and Fuelwood Collection with Transactions Costs

Based on standard household production models (see Singh, Squire, and Strauss 1986, and de Janvry and Sadoulet 2006 for reviews), we develop a theoretical model of market participation and fuelwood collection to generate testable hypotheses for our empirical analysis. Although traditional household production models focus on the intensive margin (how much to produce given constraints) using regression models with continuous dependent variables, extensive margins of market participation can also be modeled using a discrete-choice framework (Key, Sadoulet, and de Janvry 2000). We follow this approach and assume that households choose between being autarkic (self-sufficient), a seller, or a buyer of fuelwood, in order to maximize utility. Under the assumption of exogenous locations, households decide on the amount to collect in a version of the traditional household production model.[3,4] We also assume that fuelwood harvesting is open-access, a characteristic of our study area shared with resource systems in many developing economies.[5]

As in many other sub-Saharan African countries, subsistence fuelwood collection is a significant driver of forest degradation and deforestation (Angelsen and Kaimowitz 1999). Greater forest degradation leads to higher search costs associated with finding fuelwood in degraded patches. We model this as the state of the patch, S, yielding a per-unit transaction (search) cost, $t_{pc}$ (S). The presence of the proportional transaction costs lowers the effective price that sellers obtain per unit of fuelwood sold. Any household collecting fuelwood faces this proportional search cost in the model.

Additionally, a household faces fixed, lump-sum transaction costs associated with transport to the market, $t_{fc}^{m}$, and the forest, $t_{fc}^{f}$. Buying or selling households are subject to $t_{fc}^{m}$, whereas collecting households (autarkic and selling) are subject to $t_{fc}^{f}$. We assume these costs are a function of the observed distances to the market and forest, respectively, $d^m$ and $d^f$. Utility maximization in the presence of fixed transaction costs proceeds using backwards induction

[3] We assume complete labor markets. If they are not complete, the households' ability to respond to price increases in other markets may be hampered (Singh, Squire, and Strauss 1986; de Janvry and Sadoulet 2006). We also abstract from seasonality in the fuelwood extraction patterns. In this article we focus on the dry season only, because the wet season, which is when all the agricultural work takes place, may introduce labor market failures.

[4] We also abstract that (*a*) the intrahousehold distributional issues are unimportant for determining labor allocation; (*b*) all labor is homogeneous (man and women possess equal skills; family and hired labor are perfect substitutes) and is traded in a perfectly competitive labor market.

[5] We assume a period-by-period household optimization. This implies a static deterministic risk-free setting in which there is no insurance and consumption smoothing opportunities for agricultural output; we also do not allow for fuelwood to be stored across periods. These conditions reflect what we observed during our fieldwork.

(Key, Sadoulet, and de Janvry 2000). First, the household solves a continuous optimization problem for the levels of consumption and production conditional on regime (buyer, seller, or self-sufficient [autarkic]), and then solves the discrete optimization problem for the regime in which to participate by comparing the optimized variable net benefits to the fixed transaction costs of each regime.[6]

Given these assumptions, and otherwise following Key, Sadoulet, and de Janvry (2000), a household j with characteristics z maximizes utility, represented by U(), by deciding on how much of commodity i to produce ($q_i$), consume ($c_i$), and trade on the market ($m_i$, $m_i<0$ if the commodity is purchased on the market and >0 if sold on the market). We allow for only two commodities: fuelwood (subscripted by *fu*) and an agricultural good (*ag*). Further, G() is a production function that uses inputs (e.g., labor, capital) $x_i$, with $z_q$ being an exogenous productivity shifter. The price for commodity i is $p_i$, and T is an exogenous household income endowment. The parameters $\delta^f$ and $\delta^m$ equal 1 if the household reaches the forest and the market, respectively, and 0 otherwise. The utility maximization problem is therefore:

$$Max_{c_i, q_i, m_i} \; U(c_i; z)$$

s.t.

$$(1) \quad q_i - m_i = c_i$$

$$(2) \quad G(q_i,\; x_i;\; z_q) \; = \; 0$$

$$(3) \quad \delta_i^m m_i\big(p_i - \delta^f t_{pc}(S)\big) + T - (\delta^f t_{fc}^f + \delta^m t_{fc}^m) = 0$$

$$(4) \quad c_i, x_i,\; q_i \geq 0.$$

The first constraint specifies that a household cannot consume more than it produces or buys on the market (consumption constraint). The second constraint specifies the production technology for output $q_i$ (production constraint). The third constraint is the cash constraint: a household cannot spend more than it has. Denoting $\mu_{fu}$ and $\psi$ as the shadow values for the consumption and income constraints, respectively, household regime decisions may be expressed in terms of a discontinuous fuelwood price schedule:

$$p_{fu}^{m*} = \begin{bmatrix} \tilde{p} = \dfrac{\mu_{fu}}{\psi} \;\; if \;\; m_{fu} = 0 \\ p_{fu}^m - t_{pc}(S) \;\; if \;\; m_{fu} > 0 \\ p_{fu}^m \;\; if \;\; m_{fu} \; < \; 0 \end{bmatrix}$$

for the autarkic, seller, and buyer households, respectively (for expositional purposes all household subscripts have been suppressed). These prices and fixed transactions costs determine household income, conditional on regime. If $y_0 = \sum_i p_i(q_i - x_i) + T$ is the income before any transaction costs are incurred, a household buying fuelwood on the market has income $y = y_0 - t_{fc}^m$, a household selling fuelwood on the market has income $y = y_0\big(p_{fu}^m - t_{pc}(S)\big) - (t_{fc}^m + t_{fc}^f)$, and an autarkic household has income $y = y_0(\tilde{p}) - t_{fc}^f$. Note that assets like agricultural land and livestock are included in $y_0$. The income varies by household (the household index has been suppressed for expositional purposes).

The household market participation decision is based on comparing the indirect utilities from each choice (being autarkic, buying, or selling on the market; Key, Sadoulet, and Janvry 2000). The indirect utilities for the buyer, seller, and autarkic households are given by:

$$V^{buyer} = V\Big(p_{fu}^m,\;\; y_0\big(p_{fu}^m\big) - t_{fc}^m; z\Big)$$

$$V^{seller} = V(p_{fu}^m - t_{pc}(S),\;\; y_0\Big(p_{fu}^m - t_{pc}(S)\Big) - \Big(t_{fc}^m + t_{fc}^f\Big); z)$$

$$V^{autarky} = V(\tilde{p},\;\; y_0(\tilde{p}) - t_{fc}^f; z).$$

A comparison of the indirect utilities, which are a function of some critical distance to forest and the distance to market as well as prices, indicates whether a household is autarkic, a buyer, or a seller on the market.[7] The presence of fixed transaction costs delays the

[6] The two-stage utility maximization approach is also at the core of the equilibrium models in the environmental economics literature (see Kuminoff, Smith, and Timmins 2013 for a review).

[7] The transitivity of preferences assumption, which is the basis for the standard single crossing property in sorting models (Kuminoff, Smith, and Timmins 2013), guarantees that indirect utilities can cross only once. That is, for buyers, sellers, and autarkic households to co-exist in the market, the points of intersection of the indirect utilities should not coincide.

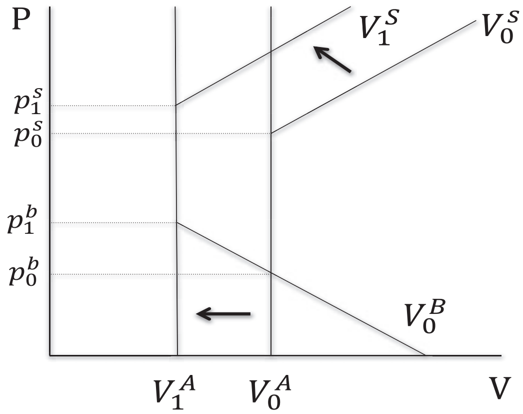


**Figure 1. Effects of separating the resource (e.g., forest) stock from the household location**

*Note*: Separating the forest from the household locations introduces fixed transaction costs associated with reaching the forest in the indirect utilities for the seller and autarkic households ($V_0^S$ and $V_0^A$, respectively). As a result, the indirect utilities shift to the left ($V_1^S$ and $V_1^A$, respectively). This results in some households being better off as buyers even when the fuelwood market prices increase from $p_0^b$ to $p_1^b$. For the selling households, the fixed transaction costs delay entry into the market until the market price increases from $p_0^s$ to $p_1^s$.

decision to sell fuelwood on the market. However, once the household has decided on being a seller, only the proportional transaction costs imposed by searching for fuelwood in a forest patch affect how much fuelwood the household is going to produce (de Janvry, Fafchamps, and Sadoulet 1991; Key, Sadoulet, and de Janvry 2000; de Janvry and Sadoulet 2006).

### *Testable Predictions*

A number of predictions emerge from this model, two of which we focus on in our empirical analysis. The first considers the effects of controlled changes in proximity to the resource:

**Proposition 1:** *Separating the resource stock from the household location makes purchasing fuelwood more attractive to some households and selling fuelwood less attractive, ceteris paribus (see figure 1).*

Including the forest fixed transaction costs lowers the income, and hence the indirect utility, for the sellers and autarkic households (represented by a shift to the left in figure 1). Whether the changes result in more households becoming autarkic depends on the functional forms.

**Proposition 2:** *Transaction costs produce a pattern of household market participation regimes in space. Autarkic households are closest to the forest, buyer households are closest to the market, and seller households are located at intermediate distances. The ordering in space holds true even when the households are not aligned along a single line. See the online supplementary appendix for a proof.*

The proposition suggests that for each household $j$ there is a critical distance to the market, $cm_j$*, that makes household $j$ indifferent between being a buyer and a seller in the market. Similarly, a critical distance to forests, $cff_j$*, exists such that the household is indifferent between being a seller and being self-sufficient. An indirect expression for these distances can be obtained by equating the indirect utilities for each type of market participation. The specific expressions for these critical distances depend on the functional forms for the indirect utilities. Note that the critical distances are household-specific and depend on the household characteristics affecting preferences, productivity, and income.

## Empirical Tests of the Model Predictions

The empirical literature on fuelwood extraction has modeled the intensive margin, namely how much fuelwood to collect, given certain household characteristics and proximity to forests (Albers and Robinson 2013). Some studies acknowledge that the household choice of whether to collect fuelwood or produce an alternative fuel introduces sample selection issues (e.g., as in Köhlin and Parks 2001; Pattanayak, Sills, and Kramer 2004) and account for sample selection using Heckman's correction method (Heckman 1979). However, these authors do not consider the option of households buying fuelwood on the market or remaining self-sufficient.

Proximity to markets is featured prominently in studies of agricultural market participation with transactions costs (Barrett 2008). These studies model household production both on the extensive and intensive margins, and typically estimate the probability that a household is going to be a producer or a supplier, and conditional on that, the amount supplied (Goetz 1992; Ouma et al. 2010). To account for sample selection in the second stage, these studies apply a version of Heckman's procedure, which most often includes calculating a (bivariate) probit of market participation, thereby generating the inverse Mills ratio, which is then used as a covariate in the model of continuous crop production. All of these studies rely on cross-sectional household survey data.

Even though theoretical work has emphasized the importance of the choice of location (i.e., forest patch) where households collect fuelwood (e.g., Robinson, Albers, and Williams 2008), only one study outside of the fisheries literature has modeled site choice for renewable resource extraction: in MacDonald, Adamowitz, and Luckert (2001), household fuelwood collection behavior is modeled in a Random Utility Model (RUM) framework, which includes proximity to forests and a detailed set of characteristics for three sites, in addition to household characteristics. However, the study does not examine the question of market participation regimes with respect to fuelwood.

Here we adopt approaches from the market participation literature. We estimate a probit model of the decision to produce fuelwood and generate the inverse Mills ratio for use in a regression model of the amount of fuelwood produced, which also depends on whether or a not a household decides to sell the collected fuelwood on the market. A key difference with previous studies is that while we have data on the quantity of fuelwood produced, we do not have data on the demand for fuelwood. We assume households make decisions about whether to participate in the market and how much to produce simultaneously. Even though previous studies show support for sequential decision-making in the context of crop production, qualitatively there is little difference between the two models (e.g., Bellemare and Barrett 2006).

As shown above, the optimal market participation regime for a household depends on the fixed components of transactions costs (the distance to the market and the distance to the forest) and proportional components (forest quality), whereas the decision on how much to produce depends only on the proportional transaction costs associated with the forest quality and the distance to the forest. We proxy the distance to markets with the proximity to trading centers (Gulu TC and Oyam TC for our sample), proximity to towns, and proximity to roads, either dirt or paved. Because of the high correlation between the distance to towns and trading centers, we present alternative specifications in the online supplementary appendix. We do not have data on forest quality, but expect it to be correlated with our proxies for markets; that is, because forests farther from roads are less accessible, we expect they will have more fuelwood.[8] While we have data on the amounts of fuelwood produced by sellers and self-sufficient households, we do not have data on the amounts of fuelwood purchased by the buyer households.

We apply a version of the Heckman selection model and estimate a system of equations for probability of fuelwood production, quantity of fuelwood, and probability of being a seller (hereafter referred to as the "cmp" procedure after the *cmp* package in Stata 14.0). Fuelwood production in this context is fuelwood collection as part of the household production model and does not include the planting of trees.

The probability of fuelwood production for household j as a function of the household characteristics, distance to markets, distance to forests, and forest quality is modeled as

$$(5) \quad y_3 = 1(z\delta_3 + v_3 > 0))$$

where $y_3$ is a scalar and equals 1 if the household is a producer of fuelwood (i.e., either a seller or autarkic) and 0 otherwise, z is a matrix of exogenous regressors including the proximity to markets variables, the proximity to forests and household characteristics (number of children, age of the household head, percentage of women in the household, whether or not the household owns a bike, and the material the house is made of); $\boldsymbol{\delta_3}$ is a vector of coefficients to be estimated, and $v_3$ is the error term. As a proxy for the proximity to markets, we use the proximity to trading centers and the proximity to roads, where a significant amount of trade takes place, especially in rural areas.

Given the spatial sorting model in the preceding sections, we expect that the probability of a household collecting fuelwood

[8] Forest quality is also correlated with the proximity to core forests and shrubland: the closer to those, the higher the quality at a forest site is likely to be. We present the results from these alternative specifications in the supplementary appendix online.

decreases with the distance to the market and increases with the proximity to forests. For this reason, we expect that the estimated coefficients on the three distance to markets variables will have positive signs and the distance to forests will have a negative sign.

The Quantity of fuelwood collected as a function of the household characteristics, proximity to forests, the inverse Mills ratio from equation (5), as well as whether or not a household is a seller, is given by

$$(6) \qquad y_1 = z_1\delta_1 + \alpha_1 y_2 + \omega\hat{\lambda} + u_1$$

where $y_1$ is the log-transformed amount of fuelwood collected, $z_1$ is a subset of the exogenous covariates matrix $\mathbf{z}$ and contains demographic variables (number of children and women within the household, age of the household head, and whether or not a house is made of bricks), $y_2$ is a binary endogenous variable indicating whether or not a household is a seller of fuelwood, $\alpha_1$ is a scalar coefficient, and $\boldsymbol{\delta_1}$ is a vector of coefficients to be estimated; $u_1$ is the error term, and $\hat{\lambda}$ is the inverse Mills ratio from equation (5).

We instrument for the endogenous decision of whether to sell fuelwood with the proximity to markets variables:

$$(7) \qquad y_2 = z\delta_2 + v_2$$

where $y_2$ is a binary variable equal to 1 if the household is a seller and 0 otherwise, $\mathbf{z}$ is a matrix of instruments that contains $z_1$ in addition to additional exogenous instruments to satisfy the identification requirements, $\boldsymbol{\delta_2}$ is a vector of estimated coefficients, and $v_2$ is an error term.

Derived directly from the model, the exclusion restriction is the proximity to markets. As the static spatial model of fuelwood implies, the proximity to markets affects the household decision of whether to produce fuelwood. Yet, conditional on a household having chosen not to be a buyer, the proximity to markets does not affect the production of fuelwood. For this reason, we use the three proxies for the proximity to markets—the distance to roads, to towns, and to trading centers—to instrument for the endogenous binary variable. As predicted by the static model, we expect that the probability of a household being a seller, conditional on producing fuelwood, decreases with the distance to markets. For this reason, we expect the coefficients on the distance to market variables to be negative. We include all exogenous variables in the selection and endogenous predictor equations (5) and (7) (Wooldridge 2002). The estimation procedure summarized by equations (5)–(7) is valid for discrete variables, without any additional distributional assumptions (Wooldridge 2002). The procedure is akin to the Heckman correction for sample selection (Heckman 1979); the difference is in the presence of the endogenous variable.

As previous studies have pointed out, the standard errors in equation (6) are likely to be incorrect as $\hat{\lambda}$ is a constructed regressor (Heckman 1979; Wooldridge 2002). This is a concern only when the coefficient on $\hat{\lambda}$, $\omega$, is statistically significant (Wooldridge 2002). Regardless of the significance of $\omega$, the coefficient estimates remain consistent (Wooldridge 2002). Because the data were collected using a multistage sampling design, sample weights are applied in the regression and the standard errors are clustered at the village level (Deaton 1997).[9]

As a robustness check, we present the results from: (*a*) a traditional two-stage Heckman probability model for the probabilities of producing and selling fuelwood; (*b*) a multinomial probit (with the choices being "autarkic," "seller," and "buyer"); and (*c*) a bivariate probit for the household decision to participate on the market as a buyer and a seller. The estimation technique models the joint probabilities of market participation for buyers and sellers, and provides estimates of the error correlation for the two equations.[10]

[9] We estimate the equations using the *cmp* package in Stata 14 (Roodman 2011). The multi-stage survey data collection for this dataset necessitates the need for adjustments for the standard errors because of clustering and the unequal probabilities of household selection. This has been achieved through the *svy* option in Stata 14. The ivreg2 command in Stata does not allow for the svy option. Yet, as a robustness check we ran the commands using pweights to account for the uneven probabilities of the households being included in the sample and the cluster option to control for intra-village correlation of the error terms. The results generated by the two commands are very similar.

[10] Additionally, we repeated the main analyses and the robustness checks using livestock variables (both binary [the availability of livestock] and counts of cattle, pigs, goats, and chickens). The results were very consistent with the main specifications. The livestock variables were also significantly correlated with other socio-economic covariates used in the analyses. For these reasons, we omit the results from the models with the livestock variables from the article. These results are available upon request.

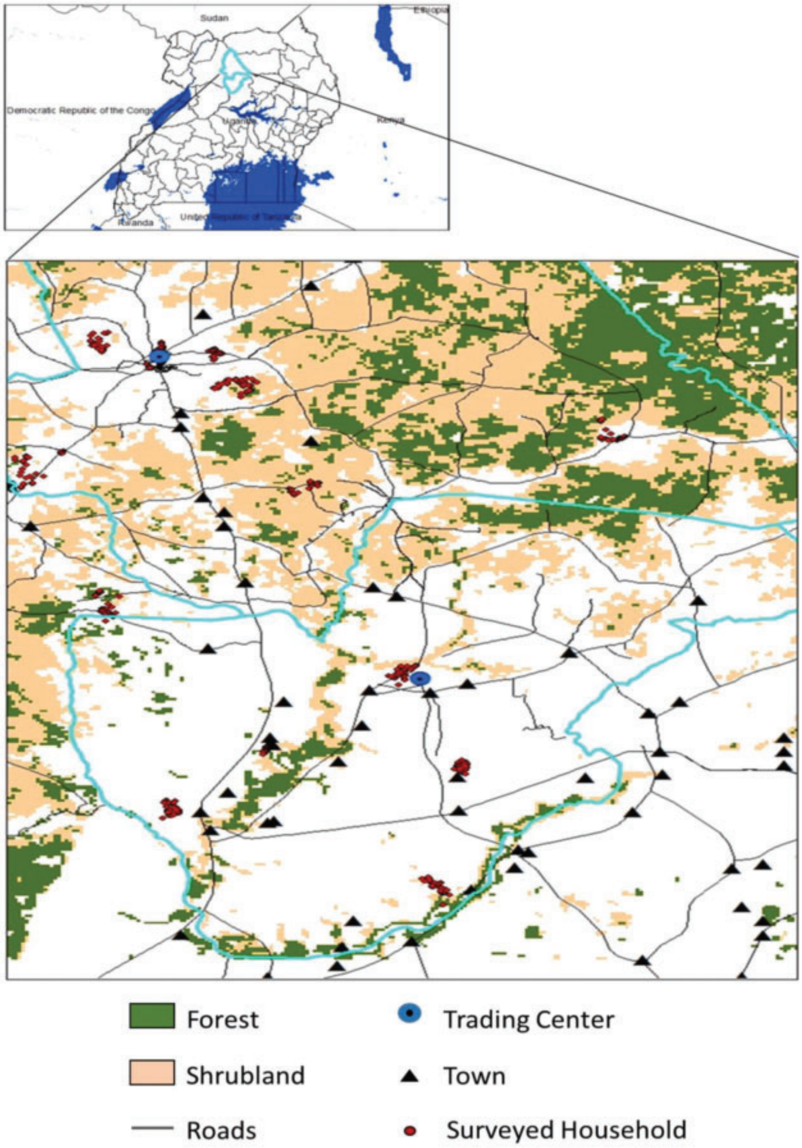


**Figure 2. Map of the study area**

*Study Area*

Covering an area of about 8,500 $km^2$, our study region spans parts of the Gulu and Oyam Districts in northern Uganda (figure 2). The nearly twenty-year conflict between the Ugandan government and the Lord's Resistance Army forced almost all of the rural population to relocate to Internally Displaced Persons (IDP) Camps (Van Acker 2004). The Oyam District was not as badly affected by the conflict; a smaller fraction of the rural households were displaced, spent less time in the IDP camps, and returned earlier (United Nations Development Program 2007). By 2007, a year after the peace treaty was signed, about 74% of the Oyam refugees had returned to their place of origin (United Nations Development Program 2007). In comparison, almost all of the rural households in the Gulu District were displaced and remained in the camps for many years, with most households returning to their original homesteads in 2009 (United Nations Development Program 2007). That households returned to their places of origin from before the war was confirmed during our field visits. In addition, our survey provides indirect evidence for this assumption, as 93% of households engaging in subsistence activities (85% of the total sample) reported doing these activities on land owned by their household, parents, or clan.[11] Exogenous placement is a key feature of the dataset, and allows us to treat the household location with respect to forests in 2006 and markets as exogenous.

Electricity in our study area is limited to cities where high prices still preclude the majority of households from using it. For this reason, fuelwood and charcoal are the most common fuel sources. Our data indicate that about 20% of the 601 households in the sample use sources other than fuelwood as their primary cooking fuels. Because few (~11%) households produce charcoal, it has been left out of the model. In aggregate, most fuelwood is collected from woodlands, although households collect some from agricultural fields when they are cleared prior to the start of each growing season.[12]

The forests (or woodlands) are comprised of *Vitex, Phyllanthus, Sapium* and *Terminalia*, or of *Butyrospermum* and *Hypparrhenia dissolute*, and wooded grasslands are dominated by communities of *Borassus* and *Hyparrhenia rufa* or of *Combretum, Terminalia, Albizia*, and *Hyparrhenia rufa* species (Langdale-Brown 1960). There is no investment in the forests in the study area. Some households plant exotic tree species consisting mostly of pine and eucalyptus, which are harvested for timber when they reach a certain age. For this reason, they cannot be considered substitutes to forests consisting of indigenous trees.

## *Socio-Economic Data*

We use geo-referenced survey data collected in 2009 (Brown et al. 2016; Brown and Kramer 2017). The questionnaire we designed was administered to 612 households in the Gulu and Oyam Districts in October and November 2009 (see figure 2). The households were selected through a multistage sampling approach. Using projected population numbers for the Gulu and Oyam Districts from the Uganda Bureau of Statistics (UBOS), the sample was first stratified between the Gulu and Oyam Districts; the second stage employed a cluster sampling procedure to select parishes (similar to counties in the United States), villages, and households to be surveyed. In particular, we randomly selected nine parishes in the Gulu District and six parishes in Oyam, with probability proportional to the population sizes projected by the UBOS. Within each parish a village was selected at random; from each village forty households were drawn at random using the household rosters maintained by the village-level local administrative official. Where the rosters were out of date, we worked with the local officials and their assistants to update the lists. Eight interviewers from the two main ethnicities in our study area administered the survey to the male or female head of the selected households.

Of the 612 completed questionnaires, we excluded ten because they lacked valid spatial coordinates. Combining the coordinates of the surveyed households with geospatial (GIS) data on the administrative boundaries, land use and infrastructure for our study area allowed us to calculate important variables pertaining to the location of the households.

## *Land Cover Data*

Our land cover data come from the GlobCover landcover dataset for 2006.[13] Since the dataset presents very detailed land cover categories, we aggregated all forest categories into a single one that includes cells with >50% tree cover and trees more than five meters in height. As a robustness check we repeated the estimation using the proximity to shrubland, a category that includes low trees (<5m in height) that do not form a dense canopy. The year the land cover data were obtained corresponds to a time prior to the households relocating from the IDP camps to their homesteads from before the war.

We lack forest quality (degradation) data. However, forest degradation is likely to be correlated with the distance variables. As a robustness check, from the geospatial data we also calculated the proximity of a household to forest cores—these are areas that exhibit very little fragmentation and are likely to be least disturbed (Fahrig 2003; Stuart

[11] Because the land markets are severely underdeveloped in the area (World Bank 2009), it is highly unlikely that whole families/clans have managed to purchase land in the few months after the refugees started leaving the Internally Displaced Persons' camps.

[12] We use "woodlands" and "forests" interchangeably to refer to areas with dense native woody vegetation that occurs naturally (i.e., not plantations).

[13] ESA/ESA GlobCover Project, led by MEDIAS-France/POSTEL, 2006. Weblink: http://ionia1.esrin.esa.int/.

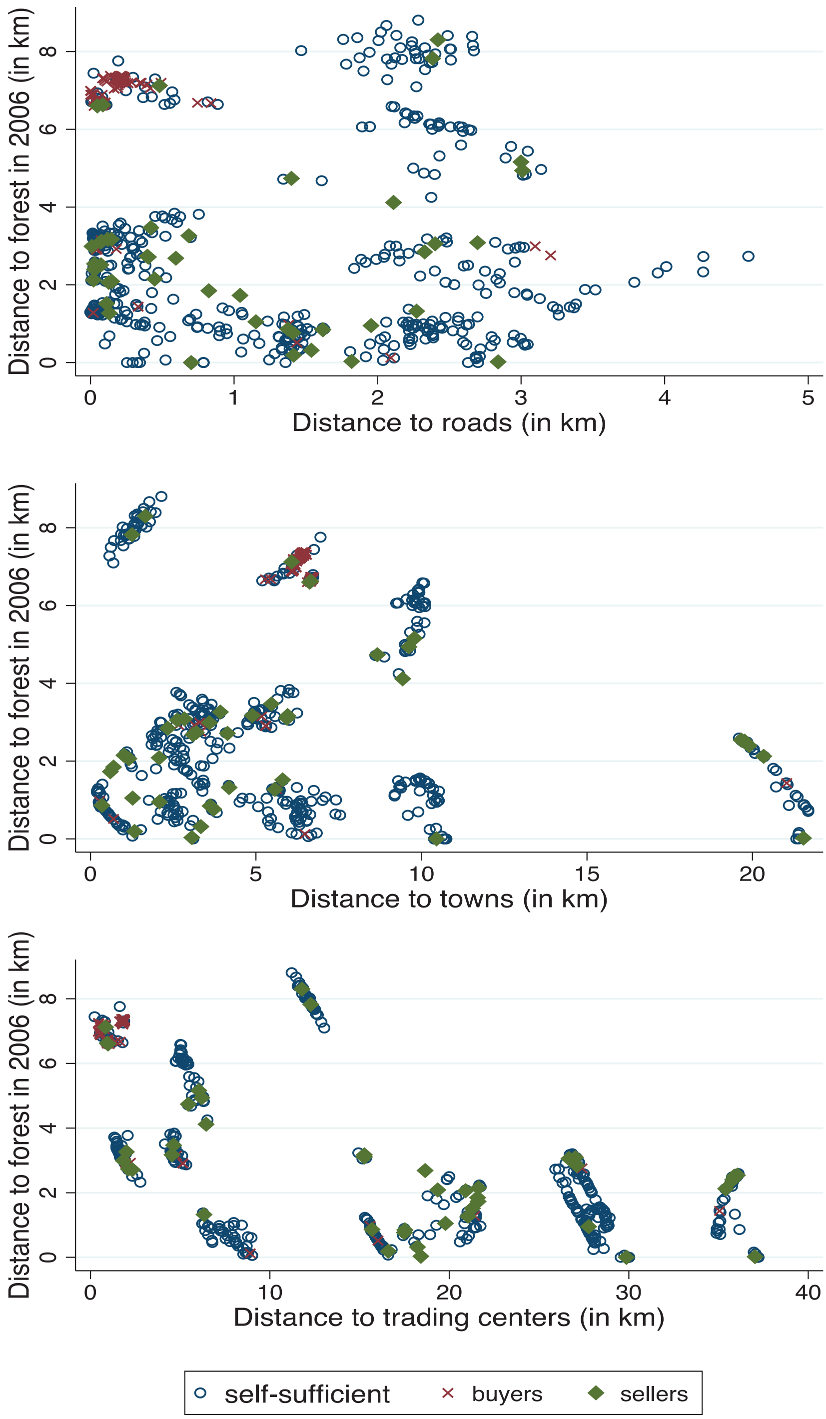




**Figure 3. Market participation regimes plotted as a function of the proximity to forests and markets**

Chapin III et al. 2011). More details on the classification of forests into core and non-core areas are presented in supplementary online appendix.

*Distance to Markets*

Fuelwood is traded on formal markets in towns and trading centers as well as along roads (either paved or unpaved). For this reason, we used the distances to roads, towns, and trading centers corresponding to 1997 as proxies for the proximity to markets. We compared the existing roads visible in publicly available aerial maps and manually drew missing segments. The trading centers are centroids for the Gulu and Oyam trading centers, the largest in the area. All the distances used in the empirical estimation are Euclidean.

## Results

Figure 3 shows scatter plots of distance to forest in 2006 versus distance to market (or road, towns, and trading centers), distinguishing buyers, sellers, and autarkic households.[14] Even before controlling for household characteristics econometrically, some clustering by participation regime is distinct. For example, the buyer households tend to be located furthest from the forests and shrublands.

Table 1 presents the descriptive statistics for our sample, applying sample weights to account for the multi-stage survey data collection design. Our sample consists of 102 buyers, forty-five sellers, and 451 autarkic households. The data suggest that the buyer households are different from the households producing fuelwood. The former have fewer children, but more adults living in the household; they are also more educated, on average. The buyer households also tend to be wealthier based on the self-reported value of a list of thirty-four household items and average annual income, as well as in terms of the type of housing (with more windows, a lower incidence of thatched roofs, and of houses made of mud bricks). These differences are significant at the 5% level. The autarkic and seller households appear homogenous in their socio-economic and demographic characteristics.

As predicted by the theoretical model, the buyer households are located closest to the market and furthest from the forest (table 1). Conversely, self-sufficient households are located closest to the forest and furthest from the market, with seller households located at intermediate distances. Surprisingly, almost all of the buyer households (96/102) are located in the Gulu District immediately adjacent to Gulu TC (93/96—in the villages of Awere Road, Gulu Prisons, and Iriaga Central; see table 2). In terms of fuelwood production during the dry season, seller households produce slightly more, but the results are not statistically significant.

The spatial distribution of the households in our sample also indicates that there are villages with only autarkic and seller households, but no buyers, as well as villages with only autarkic households (see table 2; figure 4). These results are consistent with the partial equilibrium assumption, but because of the survey data collection approach, we cannot test this observation empirically.

### *Probability of Producing Fuelwood*

The results from the binary models (equations [5] and [7]) of producing and selling fuelwood are presented in table 3. The probability of a household producing fuelwood (and not buying it) increases with the number of children (who can provide labor), if the house is made of mud bricks (indicating poorer households), and with the proximity to forests in 2006. The probability decreases with the proximity to trading centers. The interaction term bike*distance to forests is significant and positive, suggesting that if a household possesses a bicycle, it is less sensitive to the proximity to forests, effectively reducing transactions costs. This is consistent with findings that the opportunity cost of time influences fuelwood collection (Baland et al. 2010; Manning and Taylor 2014). The distance to roads variable has the expected positive sign but is statistically significant only in the *cmp* model. The interaction term of the binary "bike" indicator with the distance to roads has the expected negative sign, indicating that households are less sensitive to distances. The robustness checks in table A1 (cmp model), table A4 (first stage of Heckman model), table A6 (multinomial probit), and table A7 (bivariate probit) present consistent results across models and definitions of "forest" and "market."

### *Probability of Selling Fuelwood Conditional on Producing It*

Table 3 summarizes the impacts of variables affecting the probability of a household selling fuelwood conditional on producing it. The only statistically significant variable across the three models is the age of the

[14] Scatterplot for the proximity to shrubland is available in supplementary appendix online.

**Table 1. Descriptive Statistics for the Variables Used in the Econometric Static Household Model**

| | Autarkic | | Sellers | | Buyers | |
|---|---|---|---|---|---|---|
| Covariate | Mean | Std. Error | Mean | Std. Error | Mean | Std. Error |
| #kids | 3.18 | 0.07 | 3.42 | 0.11 | 1.87* | 0.22 |
| #adults | 11.82 | 0.07 | 11.58 | 0.11 | 13.13* | 0.22 |
| Age of the HH head (in years) | 43.91 | 1.02 | 38.90 | 0.91 | 36.88 | 2.02 |
| %females in the HH | 0.48 | 0.01 | 0.47 | 0.02 | 0.49 | 0.01 |
| 1 if HH head has no schooling | 0.12 | 0.02 | 0.13 | 0.03 | 0.06 | 0.02 |
| 1 if HH owns a bike | 0.65 | 0.03 | 0.70 | 0.08 | 0.49 | 0.07 |
| 1 if home medium-sized | 0.50 | 0.06 | 0.46 | 0.05 | 0.53 | 0.07 |
| 1 if home has no windows | 0.80 | 0.06 | 0.78 | 0.08 | 0.24* | 0.13 |
| 1 if thatched roof | 0.87 | 0.06 | 0.91 | 0.09 | 0.28* | 0.19 |
| 1 if home made of mud bricks | 0.87 | 0.04 | 0.91 | 0.09 | 0.31* | 0.16 |
| Avg. annual income (log-transformed) | 10.75 | 0.15 | 10.64 | 0.11 | 12.02* | 0.07 |
| Wealth (self-reported value of possessions, log-transformed) | 11.79 | 0.22 | 11.66 | 0.28 | 13.51* | 0.11 |
| Distance to forest in 2006, in km | 2.72 | 0.77 | 2.43 | 0.61 | 6.51* | 0.22 |
| Distance to core forest in 2006, in km | 4.58 | 0.82 | 5.96 | 0.61 | 7.89 | 0.30 |
| Distance to shrubland in 2006, in km | 1.70 | 0.70 | 1.38 | 0.41 | 3.51 | 0.25 |
| Distance to core shrubland in 2006, in km | 2.59 | 0.88 | 2.26 | 0.56 | 6.27* | 0.32 |
| Distance to trading center, in km | 16.86 | 2.65 | 17.14 | 2.14 | 2.01* | 0.87 |
| Distance to road, in km | 1.06 | 0.27 | 0.85 | 0.10 | 0.17* | 0.07 |
| Distance to towns, in km | 5.47 | 1.22 | 4.62 | 1.44 | 6.45 | 0.19 |
| 1 if in Gulu District | 0.59 | 0.08 | 0.85 | 0.09 | 0.97 | 0.02 |
| Max hours to fuelwood collection site | 1.14 | 0.07 | 1.01 | 0.09 | NA | NA |
| Bundles of fuelwood produced per typical week | 4.62 | 0.23 | 4.94 | 0.20 | NA | NA |

*Note*: Variables have been corrected for the multi-stage survey design. Asterisk * designates the variables that were significantly different for the buyer group compared to the sellers and self-sufficient households.

household head. Younger households are more likely to trade, *ceteris paribus*. The proximity to roads and trading center variables have the expected negative sign, but are not statistically significant.

The results are consistent with the robustness checks in tables A2, A4, A5a and A5b, and A7 that include multiple versions of the main specification with different proxies for the proximity to forests and markets. In all specifications the *distance to towns* variable has the expected negative coefficient, although the variable is statistically significant in only some of the models. The results also indicate that relative to the autarkic households, the seller households are located farther from forests, although only the coefficient on core forests is statistically significant across specifications.

### Marginal Effects

Our model indicates that the sample composition will change with the introduction of a policy (e.g., building new roads, creating protected areas) that affects the proximity to markets and forests. Based on the elasticities from the multinomial probit (table 4), the incremental change in the probability of a household being self-sufficient increases by nearly 50% following a one-kilometer increase in the distance to forests (table 4), *ceteris paribus*. Conversely, the incremental change in the probability of a household being a buyer nearly doubles when the proximity to forests increases by one kilometer. Although the rest of the elasticities for the key distance variables have the expected signs, none are statistically significant.

### Factors Affecting the Amount of Fuelwood Produced

The results from equation (5) are summarized in table 5. The significance of the inverse Mills ratio necessitates corrections for the standard errors (Wooldridge 2002). Because of the sampling approach, we use Jk-n jackknife adjustments for the standard errors. In

**Table 2. Distributions of the Three Types of Market Participation Regime (Buyer, Seller, or Autarkic), by Village**

| Village | Autarkic | Buyers | Sellers | Total cluster size | Distance to TC | Distance to towns | Distance to roads | Distance to 2006 forest | Distance to 2006 shrubland |
|---|---|---|---|---|---|---|---|---|---|
| Gulu District | | | | | | | | | |
| Awere Road | 11 | 29 | 2 | 42 | 1,085.41 | 6,668.56 | 119.30 | 6,542.51 | 3,765.73 |
| Peya | 24 | 0 | 15 | 39 | 18,891.83 | 2,636.38 | 773.26 | 1,719.18 | 999.30 |
| Gulu PTC | 35 | 3 | 2 | 40 | 4,762.36 | 5,218.60 | 189.68 | 3,200.60 | 1,579.51 |
| Gulu Prisons | 4 | 37 | 0 | 41 | 2,614.72 | 6,775.62 | 206.70 | 7,157.63 | 2,839.78 |
| Iriaga Central | 16 | 24 | 1 | 41 | 970.16 | 6,026.65 | 332.88 | 6,837.90 | 3,652.25 |
| Keto | 35 | 1 | 2 | 38 | 21,330.49 | 5,833.33 | 195.37 | 1,160.05 | 0 |
| Lapnyoloyo | 36 | 1 | 1 | 38 | 7,662.59 | 6,109.96 | 2,495.11 | 658.13 | 196.47 |
| Oturuoloya | 38 | 0 | 4 | 42 | 5,790.49 | 9,537.99 | 2416.04 | 5,488.27 | 1,018.18 |
| Romkituku | 29 | 1 | 5 | 35 | 35,747.93 | 20,631.09 | 678.68 | 1,586.04 | 1,143.13 |
| **District** | **231** | **96** | **32** | **359** | **10,495.80** | **6,357.30** | **607.63** | **3,582.06** | **1,802.10** |
| **Oyam District** | | | | | | | | | |
| Village | Autarkic | Buyers | Sellers | Total cluster size | Distance to TC | Distance to towns | Distance to roads | Distance to 2006 forest | Distance to 2006 shrubland |
| Abanya | 33 | 2 | 4 | 39 | 1,844.67 | 3,330.26 | 258.57 | 3,121.82 | 783.76 |
| Acampii | 39 | 0 | 2 | 41 | 12,119.31 | 1,303.75 | 2,218.76 | 7,988.67 | 7,385.81 |
| Amwa TC | 35 | 1 | 2 | 37 | 15,924.64 | 605.56 | 1,399.71 | 644.25 | 567.11 |
| Apurungo | 39 | 0 | 1 | 40 | 27,355.04 | 2,903.32 | 2,778.60 | 1,265.22 | 646.50 |
| Odebe | 36 | 3 | 3 | 42 | 26,745.78 | 2,480.87 | 2,463.33 | 2,554.26 | 2,417.88 |
| Otaga | 41 | 0 | 1 | 42 | 28,753.24 | 10,127.69 | 331.35 | 882.32 | 1,029.05 |
| **District** | **220** | **6** | **13** | **239** | **18,992.00** | **3,861.17** | **1,435.76** | **3,068.02** | **2,490.94** |

*Note*: All the distance variables represent averages per village in meters. There are some villages where only two of the types occur. Also, there appears to be a positive correlation between the fraction of buyer households in a village and the proximity to trading centers (TC). This supports our model and predictions.

**Table 3. Results from the Binary Participation Decisions**

| | CMP Procedure | | Heckman Selection | | Multinomial Probit | |
|---|---|---|---|---|---|---|
| Variable | Producer Decision | Seller decision conditional on producing | Producer Decision | Seller decision conditional on producing | Buyer relative to autarkic | Seller relative to autarkic |
| #kids | 0.22** | −0.01 | 0.23** | 0.001 | −0.29** | 0.03 |
| | (0.09) | (0.05) | (0.09) | (0.01) | (0.11) | (0.04) |
| Age of HH head | 0.002 | −0.01*** | 0.001 | −0.003* | −0.004 | −0.02*** |
| | (0.01) | (0.004) | (0.01) | (0.001) | (0.01) | (0.01) |
| %females in a HH | −0.43 | −0.02 | −0.46 | −0.03 | 0.56 | −0.03 |
| | (0.35) | (0.3) | (0.34) | (0.06) | (0.45) | (0.43) |
| 1 if house with mudbricks | 0.62*** | −0.01 | 0.60*** | 0.02 | −0.78*** | 0.28 |
| | (0.2) | (0.28) | (0.20) | (0.03) | (0.21) | (0.34) |
| Distance to Trading center | 0.04* | −0.02 | 0.04* | −0.0001 | −0.06* | −0.01 |
| | (0.02) | (0.02) | (0.02) | (0.0029) | (0.03) | (0.02) |
| Distance to roads | 1.07* | −0.24 | 1.12 | −0.01 | −1.49* | −0.16 |
| | (0.56) | (0.25) | (0.66) | (0.03) | (0.83) | (0.21) |
| Distance to forest in 2006 | −0.23*** | 0.09 | −0.24*** | 0.003 | 0.32*** | 0.03 |
| | (0.07) | (0.11) | (0.07) | (0.01) | (0.09) | (0.11) |
| Bike* Distance to roads | −0.86* | 0.17 | −0.94 | | 1.21 | 0.10 |
| | (0.45) | (0.36) | (0.55) | | (0.74) | (0.38) |
| Bike* Distance to 2006 forest | 0.05** | −0.05 | 0.05** | 0.002 | −0.067 | −0.02 |
| | (0.02) | (0.13) | (0.02) | (0.01) | (0.039) | (0.13) |
| District (1 if Gulu) | −0.64* | 0.84* | −0.61 | 0.14 | 1.04** | 1.02 |
| | (0.34) | (0.41) | (0.35) | (0.09) | (0.44) | (0.49) |
| Bike*Distance to Trading Center | | 0.01 | | | 0.01 | 0.02 |
| | | (0.01) | | | (0.03) | (0.02) |
| Inverse Mill's ratio | | −1.06 | | | | |
| | | (0.78) | | | | |
| Constant | 0.92 | −0.90 | 0.96 | 0.18 | −1.23 | −1.80** |
| | (0.86) | (0.66) | (0.84) | (0.13) | (1.13) | (0.63) |

*Note*: Standard errors appear in parentheses. All distances are given in kilometers. Significance levels are indicated as follows: ***= 1%; **= 5%, and *= 10%.

**Table 4. Elasticities from the Multinomial Probit of the Key Distance Variables on the Market Participation Regime**

| Distance variable | Autarkic | Seller | Buyers |
|---|---|---|---|
| Distance to Trading Center (km) | 0.31 | 0.05 | −1.69 |
| | (0.40) | (0.30) | (0.96) |
| Distance to roads (km) | 0.04 | −0.05 | −1.42 |
| | (0.03) | (0.21) | (1.14) |
| Distance to forest in 2006 (km) | −0.45* | −0.55 | 1.07*** |
| | (0.16) | (0.45) | (0.31) |

*Note*: Estimates not adjusted for the sampling approach. Standard errors appear in parentheses. Statistical significance levels are as follows: ***= 1%; **= 5%; and *= 1%.

**Table 5. Variables Affecting the Amount of Fuelwood Collected**

| | Original | | Bootstrap | Jackknife | |
|---|---|---|---|---|---|
| Covariate | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| #kids | 0.04** | 0.04** | 0.04* | 0.04** | 0.04** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Age of HH head | −0.004 | −0.005 | −0.005 | −0.004* | −0.005 |
| | (0.003) | (0.003) | (0.004) | (0.002) | (0.004) |
| %females in a HH | −0.26 | −0.28 | −0.28 | −0.26*** | −0.28 |
| | (0.24) | (0.24) | (0.26) | (0.05) | (0.30) |
| District (1 if Gulu) | −0.31*** | 0.02 | 0.02 | −0.31* | 0.02 |
| | (0.09) | (0.12) | (0.13) | (0.12) | (0.14) |
| 1 if house made of mudbricks | 0.12 | 0.10 | 0.10 | 0.12 | 0.10 |
| | (0.10) | (0.10) | (0.12) | (0.06) | (0.11) |
| Distance to forest in 2006 | −0.09** | −0.03 | −0.03 | −0.09*** | −0.03 |
| | (0.03) | (0.02) | (0.04) | (0.02) | (0.03) |
| Bike* Distance to 2006 forest | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.02) | (0.02) | (0.03) | (0.01) | (0.02) |
| 1 if HH sells fuelwood | 0.03 | −0.02 | −0.02 | 0.03 | −0.02 |
| | (0.40) | (0.42) | (0.83) | (0.34) | (0.64) |
| Inverse Mills ratio | −0.49** | −0.43*** | −0.43 | −0.49 | −0.43 |
| | (0.12) | (0.18) | (0.34) | (0.38) | (0.24) |
| Constant | 1.69*** | 1.52*** | 1.52*** | 1.69*** | 1.52*** |
| | (0.23) | (0.18) | (0.24) | (0.22) | (0.15) |
| Village fixed effects | Yes | No | No | Yes | No |

*Note*: Log-transformed, standard errors appear in parentheses. Significance levels are as follows: ***= 1%, **= 5%, and *= 10%.

addition, we provide estimates from a bootstrap that accounts for the multi-stage survey design and uses 100 replications (Kolenikov 2010). Note that because of the relatively small number of villages, the runs of specifications with village fixed effects for the amount of fuelwood collected are not always possible. For this reason, we consider model 5 to be the official specification with corrected standard errors.

Our results indicate that the number of children within a household is associated with more fuelwood collected. Given that women and children primarily collect fuelwood in our study area, this is not surprising. The distance to forest in 2006 and the binary variable indicating whether a household sells fuelwood both have negative but insignificant coefficients, which may be due to the small number of sellers relative to the self-sufficient households in our sample.

## Conclusions

This study adds to the literature on fuelwood collection by modeling households' market participation regime as a function of their location with respect to forests and markets. We adapt the static agricultural household production model with transaction costs to the fuelwood setting in which the household resides apart from locations of markets and forests. We find that the distances to markets and the forest resource sort households into market participation regimes. Our predictions about households—buyers closest to the market, autarkic households closest to the forest, and sellers located at intermediate distances—are supported by empirical evidence from northern Uganda. A limitation of our study is that the survey was not specifically designed to target the spatial patterns of household market participation, which could lower the power of the statistical analysis and account for some of the statistically insignificant results. Despite this limitation, we still find statistically significant spatial patterns of fuelwood production.

A few existing papers examining forest loss make claims similar to ours. However, previous work has either applied an optimal stopping framework that models forests as continuous and not comprised of discrete patches (e.g., Robinson, Williams, and Albers 2002; Robinson and Lokina 2011) or has focused on the discrete choice of a forest patch for collection without modeling the endogenous choice of market participation regime (e.g., Robinson, Albers, and Williams 2008; Robinson and Lokina 2011; Kohlin and Amacher 2005). Because of the flexibility of the discrete-choice framework, we can combine the choice of market participation with heterogeneity of the landscape comprised of discrete markets, forest patches, and households, the location of which is unconstrained by the model.

Our model has specific implications for the impact evaluation of conservation and development policies. Although studies from the impact evaluation literature find spillovers from different land conservation policies (e.g., Andam et al. 2008; Alix-Garcia, Shapiro, and Sims 2012), few model the mechanisms through which spillovers from policies emerge (Robinson, Albers, and Williams 2011; Robinson and Lokina 2011; Lopez-Feldman and Wilen 2008). Impact evaluations of protected areas, as a result, assume that spillover effects occur in locations immediately adjacent to protected areas and test for the presence of spillover effects by using arbitrary distances, for which no theoretical justification exists (Miteva, Pattanayak, and Ferraro 2012; Robinson, Albers, and Williams 2011) Yet a re-sorting of market participation regimes implies that policy-induced changes in forest degradation will not necessarily manifest in patches adjacent to or nearby protected areas. Depending on the proximity of households to natural resources, some patches are going to be more heavily exploited than others (López-Feldman and Wilen 2008; Smith, Sanchirico, and Wilen 2009; Robinson, Albers, and Williams 2008). At the same time, proximity to the market can also influence the intensity of resource exploitation (Liese, Smith, and Kramer 2007). In our case, this latter effect is transmitted through the choice of market participation regime. Our approach could be used, for example, to make forecasts of potential spillover effects from the introduction of a conservation policy like protected areas, as some of the fisheries literature has done in analyses of marine protected areas (e.g., Smith and Wilen 2003). Implementation of protected forest areas (i.e., the removal of forest patches from households' choice sets) would result in households re-sorting their market participation decisions across the landscape, not only adjacent to the protected areas. Our model allows us to predict which households are likely to be impacted and in what way. For example, if the distances to the nearest forest patch become too long, households may choose to buy fuelwood rather than collect it; others may switch fuelwood collection to a different forest patch. Understanding household spatial behavior can help mitigate the spillover effects on unprotected forest patches.

More broadly, this research illustrates the policy relevance of considering non-local spatial linkages in resource-use regimes. Disturbances in a coupled human-natural system, for example, a new policy, can induce non-marginal changes in the spatial patterns of the system. These changes can be transmitted through market or non-market values, with the magnitudes of impacts depending on the scale, the type of disturbance, and the attributes of the system (Kuminoff, Smith, and Timmins 2013). Changes in spatial attributes have non-local impacts on the spatial patterns of human behavior, which in turn modify the natural environment (Kuminoff, Smith, and Timmins 2013; Klaiber and Smith 2013; Smith et al. 2014). Non-local effects, in turn, indict standard quasi-experimental approaches to policy evaluation, in which distance-based metrics are used to separate treated and control sites and identify spillovers (Smith et al. 2014; Robinson, Albers, and Williams 2011; Miteva, Pattanayak, and Ferraro 2012). In our case, a policy such as a protected area, a road that lowers transportation costs, or an exogenous price change for fuelwood could all trigger a resorting of households into new market participation regimes. By modeling household market participation decisions as a function of the proximity to markets and forest stocks, our work allows us to identify the relevant scales of impacts and thus control groups unaffected by a treatment. For this reason, our work has direct implications for conducting impact evaluations.

Such non-local spatial linkages may have important implications for reduced-form econometric techniques for impact evaluation. Specifically, non-local spillovers may in some contexts contaminate the formulation of control groups in quasi-experimental methods. This raises questions about how to construct the statistical counterfactual to identify the treatment effect of a protected area. Our modeling approach follows spatial-dynamic bioeconomic models that use a discrete-choice framework to model harvester decisions (Smith, Sanchirico, and Wilen 2009). In an application to fisheries management, a sorting mechanism like this recently was shown to invalidate spatial identification strategies in treatment effects models (Smith et al. 2014). In their application, the sorting behavior of resource extractors over space leads to a violation of the Stable Unit Treatment Value (SUTVA) assumption required for identification in the causal model. While spatial-dynamic fisheries models typically include both the meta-population dynamics and the sorting mechanisms, SUTVA violations can occur in the absence of spatial migration of the resource base if harvester sorting behavior feeds back on the stock (Smith et al. 2014). Analogous effects could arise when evaluating protected forest areas: our model could alert analysts to potential SUTVA violations, and improve treatment-control pairings for evaluating the impact of protection. Thus, we echo previous calls that policy evaluation needs to consider the mechanisms in order to be able to understand and contribute to conservation and development (Deaton 2010; Miteva, Pattanayak, and Ferraro 2012).

## Supplementary Material

Supplementary material is available at *American Journal of Agricultural Economics* online.

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