Household bargaining over technology adoption

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1 Introduction

According to the World Health Organization (WHO), pollution from households' traditional cooking technologies is the leading environmental cause of death in developing countries (Martin et al., 2011; WHO, 2009a). The burning of biomass in traditional stoves or in an open stone fire produces large amounts of harmful chemicals and respirable particulate matter that are responsible for an estimated 1.5 million deaths annually (WHO, n.d.; Smith et al., 2006; Naeher et al., 2007). The adverse health impacts are disproportionately concentrated among the poorest, who typically use biomass or coal as fuel for cooking and heating. Among those that are vulnerable, women and their children are at a higher risk because women often are primarily responsible for cooking in developing countries (Bruce et al., 2000; Dasgupta et al., 2004). In particular, almost half of the mortalities due to biomass burning are among children under age five and 60 percent of the adult mortalities consist of women (UNDP, 2009; Bruce et al., 2002).

It has been shown that these health risks are dramatically reduced by replacing the traditional technologies with modern cook stoves (MCSs, biomass stoves that are equipped with ventilation chimneys or non-biomass stoves fueled by gas or electricity). Relative to traditional stoves, MCSs significantly reduce the risk of respiratory illnesses in both children and women (e.g., Smith et al., 2011; Dherani et al., 2008), the exposure of pregnant women to carbon monoxide, and the occurrence of adverse neonatal outcomes (e.g. Thompson et al., 2011; Pope et al., 2010). MCSs, due to their higher energy efficiency can also reduce the quantity of fuel required by the household, thereby reducing the time spent collecting fuel, and cooking, with salutary effects on women's time, productivity and household income (Barnes et al., 1994).

While there is now substantial evidence that women are disproportionately affected by the adverse effects of traditional cooking technologies relative to men (e.g., see Ezzati and Kammen, 2002; Balakrishnan et al., 2002), their influence over the relevant household technology choice - whether or not to use a biomass stove - is still not well understood. To the extent that women assign higher values to MCSs than men, and that women can have a greater impact on household purchase decisions through more effective bargaining and negotiation, initiatives that seek to increase MCS adoption would be more successful if they marketed and disseminated stoves in a way that, as a byproduct, also contributed to the empowerment of women. Understanding the linkage between gender and purchasing decisions is becoming increasingly important since MCS adoption

rates in developing countries remain very low despite years of stove dissemination programs and global attention paid to the issue (Mobarak et al., 2012).

Our specific objective is to examine the effect of women's influence over household economic decisions in household energy technology choice. We develop a conceptual model of intra-household decision-making based on a collective household model, with MCS adoption as the outcome of bargaining among male and female members of the household. We empirically examine the effect of women's intra-houshold power or authority over the MCS adoption decision using a nationally representative dataset collected in 2005-06, with information on stove choice by more than 25,000 households drawn from 1445 villages in rural India. The data also contain detailed information, not commonly collected in nationally representative surveys, on women's decision making authority and gender relations within the household. We use survey questions on whether or not a household owns a biomass stove (and uses biomass as fuel) to specify a binary indicator of MCS adoption. We construct a proxy for women's empowerment, using information on male vs female decision-making authority in the purchase of household appliances. Our empowerment indicator consists of four ordered categories: whether the purchase decision is made by males only; by males primarily with input from females; by females primarily with input from males; or by females only. Our use of decision-making authority as a proxy for empowerment is consistent with other studies such as Patel et al. (2007), who used indicators of whether or not women could make decisions about food preparation and consumption to represent intra-household bargaining power.

Our conceptual and empirical model is different in two important ways from models commonly used in studies of intra-household bargaining power effects on household (adoption) decisions. First, a standard approach is to include a variable related to bargaining power (or a gender specific variable) directly as a covariate in the adoption equation (e.g. El Tayeb Muneer and Mukhtar Mohamed, 2003). Identification of the effect of power within this framework, however, is problematic because it is likely that unobservables that affect adoption and empowerment are correlated (see Maddala, 1983). Our model and approach is different in that we have a binary outcome equation (adoption) with a ordered discrete covariate (women's empowerment indicator) which may possibly be endogeneous. We jointly estimate our adoption-empowerment system (a probit - ordered probit model) using FIML methods (Greene and Hensher, 2010), and account for the

endogeneity of empowerment through the errors of the two equations. Our data provide sufficient information to identify the two equations. The decision problem of interest to us is different from the kind conventionally analyzed using a Heckman-type model, in which a continuous outcome is specified as a function of a binary regime-switch variable.

A second novel feature of our approach is that it distinguishes between alternative hypotheses about the role that women play in relation to specific household purchasing decisions. In essence, we address, in the context of MCS adoption, the question: "do women have influence over adoption?" This question is conceptually distinct from the related one: "do women have an influence over adoption due to their intra-household bargaining power?" The distinction turns on whether or not, with respect to a particular purchasing decision, an individual woman can affect, through bargaining and negotiation, the extent to which her preferences prevail within her household's joint decision-making process. At one extreme, a woman may have either a great deal of, or very little, influence over a particular decision, but in either case, the magnitude of her influence is determined by factors such as societal norms and cultural traditions, over which the individual woman has absolutely no control. That is, a woman may be either empowered or disempowered with respect to a specific kind of decision, not because she is either strong or weak relative to the males in her household, or because she is either skillful or ineffective at household bargaining, but rather because, simply, "this is the way things are" within her social milieu. For example in many cultures, women decide on matters relating to children's health while, men, exclusively decide on capital expenditures. At the other extreme, the influence that a woman has within a particular household may vary widely from one household to another, depending on idiosyncratic aspects of the relationship between the males and females within that particular household (e.g., education differences between men and women). In this respect, our paper makes a novel contribution to the empirical bargaining literature, which does not distinguish between these two alternative hypotheses about the source of women's influence. As far as we are aware, we are the first to specify a model which leaves open either of these possibilities, and then tests empirically which of them is more consistent with the data in our particular application.

The two possibilities have quite different policy implications. If women care more about clean stoves but the amount by which they can influence the household decision-making is exogenously determined, then

women's differential role in the allocation of resources to MCSs will largely be determined by the social norms that govern this influence. Adoption programs under this scenario may be able to increase uptake by targeting women, but their success will be limited by traditions, culture and institutional constraints. More profound modifications of institutions and social norms would be required to mobilize women's' differential preferences for MCSs. If on the other hand, the extent of a woman's influence is limited only by her ability to negotiate with the men in her household, then policy interventions can potentially increase adoption by empowering women. This implies, for instance, that if governments provide financial assistance to poor households for energy innovations, then to the extent that a woman's bargaining power is endogenous, and is enhanced when she, rather than the man, is the recipient of financial assistance, then cookstove adoption will tend to increase when financial assistance is directed to the woman in the household rather than the man. Similarly, to the extent that gender wage and labor-force participation gaps are among the determinants of intra-household bargaining power, promoting gender equality by closing these gaps could, even without specific energy interventions, potentially increase stove adoption rates.

2 Conceptual model

We consider a household with two decision-making agents, a man (m) and a woman (f). We assume for simplicity that there is a single private, and a single public, good. The private good is denoted by x. The public good, which is consumed jointly by both agents, is indoor air quality, or, equivalently, the absence of indoor air pollution, s (for 'smoke'), which generates disutility for both agents. Men and women are assumed to have different, preferences over the two goods, since fuel collection costs associated with the production of s, and exposure rates to smoke, differ significantly between men and women. For $i = m, f$, we assume that individual i has a quasi-linear utility function $u_i = x - \psi_i(s)$ where ψ_i is i's disutility from smoke. We assume $\psi_i' > 0$ and $\psi_i'' > 0$. Our restrictions on ψ follow Basu (2006), who used a strictly convex function to depict the disutility that parents incur from child labor. In our context it implies that the effect of smoke on household members cumulates over smoke levels - an individual may simply dislike a small amount of smoke while larger amounts may be unbearable. Based on an extensive literature (cites), we assume for now that $\psi_f'(s) \geqslant \psi_m'(s)$, i.e., that the marginal disutility of smoke is at least as great for women as men.

Household decision-making making is assumed to be cooperative, leading to pareto efficient outcomes. Thus, the household utility function can be written as a weighted sum of individual utilities of household members (Browning and Chiappori 1998). Specifically, the household maximizes:

$$U = \delta(\lambda)(x - \psi_f(s)) + (1 - \delta(\lambda))(x - \psi_m(s)) \tag{1}$$

where $\delta(\lambda) \in [0, 1]$ represents a woman's weight in the household utility function. λ which represents a woman's authority or empowerment in the household typically will depend upon on a set of individual, household and community characteristics, and social norms that create gendered endowments of empowerment in different spheres of household decision-making. Normalizing all prices to one, reflecting constant prices across a cross-section of households, the budget constraint of the household is given by:

$$x + \Gamma(s) = w \tag{2}$$

where w is household wealth, and $\Gamma(s)$ is a technology that the household can purchase from the market to reduce the level of smoke in the household. Letting $\overline{s}$ denote the level of smoke if no technology is purchased, the technology is assumed to have the property:

$$\Gamma'(s) = 0, \text{ for } s \geqslant \overline{s}, \text{ and for } 0 \leqslant s \leqslant \overline{s}, \Gamma'(s) < 0, \Gamma''(s) < 0 \tag{3}$$

The concavity of Γ in smoke levels implies that Γ is convex and increasing in smoke *mitigation*. That is, letting m $= \overline{s} - s$ denote the level of smoke reduction relative to no purchase, $\Gamma(s) \equiv \Gamma(\overline{s} - m)$ is clearly increasing and convex in m. Further, to guarantee an interior solution we assume that $lim_{s \nearrow \overline{s}} \Gamma'(s) = 0$ (it is essentially costless to buy a miniscule amount of the technology) $lim_{s \searrow 0} \Gamma'(s) = \infty$ (it is prohibitively expensive to reduce smoke to zero).

Substituting the budget equation (2) into the utility function (1), we obtain

$$U = \delta(\lambda)(w - \Gamma(s) - \psi_f(s)) + (1 - \delta(\lambda))(w - \Gamma(s) - \psi_m(s)) \tag{4}$$

Maximizing (4) yields the following first order condition:

$$\text{FOC}(\lambda, s) = \delta(\lambda)\psi'_f(s) + (1 - \delta(\lambda))\psi'_m + \Gamma'(s) = 0 \tag{5}$$

Our interest is in deriving an expression for the effect of empowerment on s. Using the first order condition corresponding to consumption of the public good (equation 5), and implicitly differentiating, we get:

$$\frac{ds}{d\lambda} = -\frac{\frac{d\text{FOC}}{d\lambda}}{\frac{d\text{FOC}}{ds}} = -\frac{\delta'(\lambda)(\psi'_f(s^*) - \psi'_m(s^*))}{\delta(\lambda)\psi''_f(s^*) + (1-\delta(\lambda))\psi''_m(s^*) + \Gamma''(s^*)} \tag{6a}$$

$$:= \text{DEN}(\lambda, s^*)\delta'(\lambda)(\psi'_f(s^*) - \psi'_m(s^*)) \tag{6b}$$

where the term $\text{DEN}(\lambda, s^*)$, the reciprocal of the denominator in (**??**), is unambiguously negative given our assumptions about household utility weights, individual utility functions and the technology. (Note that $-\text{DEN}(\lambda, s^*)^{-1} > 0$ is larger, the more convex is either household member's disutility from smoke, and smoke reduction technology. So the sign of $\frac{ds}{d\lambda}$ turns on the differential preferences between men and women for consumption of the public good. That is, $\frac{ds}{d\lambda}$ is positive iff both $\psi'_m(s^*) < \psi'_f(s^*)$ and $\delta'(\lambda) > 0$. The following result follows immediately:

Proposition 1 *Policies that can increase a women's bargaining power/authority within the household will reduce indoor air pollution if and only if (a) women's preferences for smoke mitigation is stronger than men's, and (b) if women's household utility weights are strictly increasing in their bargaining power/authority.*

3 Literature

Surprisingly few studies have examined the barriers to households' adoption of MCSs in developing countries. In a recent review, Lewis and Pattanayak (2012) argue that the conceptual basis of the MCS adoption literature remains "thin, narrow and scattered" and that it has failed to deliver systematic evidence on the role of determinants such as intra-household dynamics, household composition and headedness, and gender roles. Much of the published literature on this issue regards households' decision to adopt MCSs as the result of a single decision-maker's actions. An individual's ability to negotiate intra-household resource allocations that are more consistent with her own preferences is not stressed. The emphasis is instead on the effects of standard demand side determinants.

Consistent with the standard technology adoption literature (Barnes 1994; Fuglie and Kascak 2000), Amacher et al. (1992) and Jan (2012) show that household wealth is a primary determinant of MCS adoption. Relatedly, Edwards & Langpap, 2005 show that households' living in communities with better

access to credit are more likely to adopt. Education of the head and literacy levels of household members are also important since higher education and experience enable consumers to interpret information and value the benefits of an improved technology (Slaski and Thurber (2009); EPA (2004), Shanko et al. (2009) and Yosef (2007). According to Beyene and. Koch (2012) households with female heads and those with a larger proportion of children are more likely to adopt MCSs, relative to either male-headed households or households without children, since the adverse consequences of biomass stoves are particularly acute for women and children. Gebregzabiher et al. (2012) show that after accounting for income, education, age and occupation of the household head, larger housholds are more likely to adopt. Caste and religious affiliations of households also can affect MCS adoption by creating differentials in the diffusion of information and access to dissemination programs among minorities (Stewart (1987).

The literature is mixed on the extent of women's influence on the decision to adopt MCSs. One view is that although women are often in charge of cooking, household purchases are made by male members and women play a minimal role in influencing household technology adoption decisions (e.g. Jan, 2012; Rai and McDonald, 2009). Others such as El Tayeb Muneer and Mukhtar Mohamed (2003) have found the socio-demographic characteristics of female household members to be significant in regression models of MCS adoption, even in cases where household decision-making was concentrated in the hands of men. Duflo et al. (2008)using household level data from a state in India found a positive association between female savings accounts and the adoption of clean stoves. Miller and Mobarak (2011) using a field experiment involving about 3000 households in 60 Bangladeshi villages found that women have a higher preference for improved stoves, but lack the authority to make purchases. The authors conclude from this that policies will not be able to exploit women's higher preferences for MCSs without a broader social change that empowers women. According to Kammen (1995) the failure of policy design in taking these contextual factors into account is responsible for the low observed rates of MCS adoption in many regions. These views also resonate the with a broader literature on technology diffusion which emphasizes the importance of recognizing the decision making context and values and norms of potential adoptors (Surry and Farquhar, 1996; Glasgow et al., 2003; Stockdill and Morehouse, 1992; Rogers, 2010).

In general the unitary household model of household is rejected (see Browning and Chiappori 1998;

Thomas 1994). Models of bargaining developed by Manser and Brown (1980) and McElroy and Horney (1981), and collective household decisionmaking (Chiappori 1988, 1992) which recognize individual preferences and intra-houshold bargaining are considered more realistic. The importance of individual preferences has also been demonstrated empirically. Bargaining power held by women in a household is associated with improved well-being of women and, specifically, the health and education of their children (Doss; duflo, Haddad & Hoddinott 1994; Rubalcava, Teruel & Thomas 2004; Thomas 1994).

4 Data and study context

The data are drawn from the India Human Development Survey (IHDS), undertaken by the University of Maryland and the National Council of Applied Economic Research (see Desai et al, 2007) The IHDS is a nationally representative survey conducted in 2005-2006 which spans over 1503 villages and 971 urban area blocks and encompasses 41,554 households with 215,753 people. The data contain detailed information on individual and households' socioeconomic and demographic characteristics, education, employment, economic status, social networks and gender relations. IHDS also includes a module with information on economic and social variables on villages where the households' are located. For our analysis we focus on rural India. Our sample consists of 25427 households in 1445 villages drawn from all 33 states in India. The IHDS sample was selected using a clustered sampling design. Since the data are not drawn from a random survey of the Indian population, multipliers representing survey probabilities for each household are included in the survey information to make the sample nationally representative We use these multipliers in our econometric analyses.

We define MCS as a stove that does not burn using biomass fuels including coal, or a stove that burns on biomass but designed with a chimney. One module of the survey collected detailed information on the type of biomass stove and fuel used by a household. Households were categorized into one of four categories: a). not owning a biomass stove, that is, they used an LPG or electricity powered stove b) owning an improved biomass stove equipped with a chimney, c). owning a traditional biomass stove without a chimney, d) or cooked with biomass on an open fire. We paired the information on stove ownership with actual biomass and other solid fuel use (coal or charcoal, dung, firewood, crop residue) to separate out households that owned

a biomass stove but did not burn biomass. Using this approach we defined households as adoptors of MCSs if they did not own a biomass stove or they owned an improved biomass stove equipped with a chimney (categories a and b).

The survey also directed detailed questions about gender relations and intra-household power to a woman in each household who had been married at least once. One question provides information regarding the purchase of household items and decision making authority held by male and female members of the household. Decision making authority was recorded as belonging to several categories based on whether the decision was made by males, females or jointly. We use this information to create a proxy for empowerment based on women's decision making authority regarding purchases of household items.

The survey also includes detailed information related to each household's socioeconomic characteristics, such as income age, education level, gender and occupation of the household head and other members. Information on social networks and community characteristics of households is also available. The survey also provides an index of wealth or long term economic status of a household based on information on goods and assets the household owned and the quality of housing.

India provides a natural context for our study. India dominates the global pattern of household biomass use in absolute numbers, with almost 740 million people, comprising of 70 percent of the population in the country, using biomass as their primary energy source for cooking and heating (General, 2001; Reddy and Srinivas, 2009). Over 72 per cent of the population still lives in rural areas. In rural India, more than 90 per cent of households use biomass fuels such as dung, firewood, coal and crop residue for household energy needs. Indoor air pollution from households' biomass accounts for 4 to 6 percent of the national burden of disease and an estimated 500 thousand premature deaths occur annually due to the use of biomass fuels among the poorest and most vulnerable populations of the country (Smith, 2000). A number of government and NGO initiatives have been launched to reduce these risks through the introduction of MCS technologies into households. [1] Despite these efforts, MCSs adoption rates remain very low in India (e.g., Balakrishnan et al., 2002; Parikh et al., 2001).

[1] For instance, the National Programme for Improved Cookstoves, introduced in the early 1980s, subsidized producers and offered households improved stoves at reduced prices.

5 Empirical Framework

5.1 A model of household MCS adoption with endogenous empowerment

Our objective in this section is to empirically estimate the effect of empowerment on adoption. To guide our empirical approach we draw on proposition 1 and derive testable hypothesis. From equation (6a),

$$\frac{ds}{d\lambda} = \text{DEN}(\lambda, s^*)\delta'(\lambda)(\psi'_f(s^*) - \psi'_m(s^*)) \tag{7}$$

Using this expression we consider the change in s due to a finite change $\triangle\lambda$. To get a first order approximation to this change, we evaluate the differential at the magnitude of the change, i.e.,

$$\triangle s \approx \frac{\partial s}{\partial \lambda}\triangle\lambda = \text{DEN}(\lambda, s^*)\delta'(\lambda)(\psi'_f(s^*) - \psi'_m(s^*))\triangle\lambda \tag{8}$$

Equation (8) poses a composite hypothesis that we can test using our data. A statistically significant estimate of empowerment implies both: (a) the utility gain to women from adoption is strictly greater than that for men. and (b) women's empowerment is one of the determinants of the household's decision to adopt MCSs.

We examine a household's decision to adopt MCSs using a probit specification. Our observed indicator of adoption, ν_i, is a binary variable, which takes a value of one if household i uses a MCS and zero otherwise. To model this binary choice, we use a standard probit specification, assuming that the observed binary purchase decision is linked to unobserved, continuous variable, ν_i^* representing the extent of the household's efforts to abate the effect of smoke.

Consider which represents the unobserved benefit or utility gain to household i from adopting a MCS:

$$\nu_i^* = \alpha + \beta\lambda_i + \boldsymbol{\gamma}'\mathbf{X_i} + \varepsilon_i^v, \tag{9}$$

$$Prob(v_i = 1|\lambda_i, \mathbf{X_i}) = \Phi(\alpha + \beta\lambda_i + \boldsymbol{\gamma}'\mathbf{X_i}) \tag{10}$$

The intercept term, α, represents utility gains to the household from adoption that are not explained by the explanatory variables. The explanatory variables in equation 1 include a proxy for women's empowerment, λ_i (an ordered indicator indicator with four levels), and a set of household characteristics, $\mathbf{X_i}$ that affect adoption through coefficients β and $\boldsymbol{\gamma}'$, respectively. If the idiosyncratic influences on adoption - i.e.,

the $\varepsilon_i^{v\prime}$'s - are assumed to be independent draws from a standard normal distribution and uncorrelated with the explanatory variables, the parameters of equation 1 can be estimated consistently using a probit model. However, if adoption and empowerment are driven by unobservables that are correlated, then equation 1 violates the assumption that regressors are uncorrelated with the error term, that is, λ_i is endogenous in the adoption equation. In this case, the causal effect of empowerment power on adoption will be conflated with the effect of unobservables that affect both empowerment and adoption.

Standard methods designed to yield consistent estimates of parameters in the presence of endogeneity have limited use in our context because of the nonlinear form of equation 9. If the outcome variable were continuous, consistent two-stage estimation of the adoption equation would still be possible, either through instrumental variable methods when the endogeneous covariate is continuous, or through an endogenous regime-switching model when the endogeneous covariate is binary (see Heckman 1978).[2] When the outcome variable is not continuous (e.g., binary, as in the case with adoption), standard two-stage Heckman-type of estimators are no longer applicable due to the nonlinearity of the model. Moreover, full information maximum likelihood estimation (FIML) of binary dependent variable models with endogenous binary covariates are difficult to implement and has often led researchers to ignore endogenous switching (Miranda and Rabe-Hesketh, 2006).

For instance, we cannot rely on two-stage instrumental variable methods they are based on moment conditions that are defined by linear expectations, variances and covariances (Greene oc; Miranda and Rabe-Hesketh, 2006 Heckman 1978; de Ven and Praag 1981; Wooldridge 2002). An alternative solution, that accounts for nonlinearity and, thereby, is commonly, used in the context of discrete choice models, involves obtaining the residuals from a linear regression of empowerment in the first stage, and adding the residuals as an explanatory variable in the second stage adoption equation (e.g., see Rivers and Vuong 1988). However, these approaches assume a linear first stage model. Since we observe empowerment as a non-continuous outcome in our data, the nonlinearity of the first stage equation prevents us from using the residual based approach as well.

[2] Simple two-stage regression procedures have been developed to estimate the latter model, where probit estimates of the endogeneous dummy or switch equation are first obtained and the estimated parameters are used to augment the second stage linear regression model of the continuous outcome variable.

Instead we account for endogeneity by estimating the empowerment equation separately although not independently from the adoption parameters using full information maximum likelihood (FIML) (see Greenexx). Our framework is comparable to a two stage model where the conditional expectation, obtained as predicted values from a first stage empowerment equation, is used to replace λ_i in the second stage adoption equation. However, unlike two stage methods, the FIML approach accounts for the correlation between errors of adoption and empowerment.

To model the discrete nature of our observed empowerment variable, λ_i, we use a standard ordered probit specification. Specifically, we assume that the observed levels of women's power λ_i are linked to an unobserved continuous scale of women's empowerment,

$$\lambda_i^* = \mathbf{b}'\mathbf{Z}_i + \varepsilon_i, \tag{11}$$

where the $\mathbf{Z}_i$ include a constant term and a set of variables that affect women's intra-household empowerment. Assuming that the random disturbances, ε_i, have a standard normal distribution, the probability that a woman in household i is observed in power category j is:

$$Prob(\lambda_i = j) = \Phi(\mu_j - \mathbf{b}'\mathbf{Z}_i) - \Phi(\mu_{j-1} - \mathbf{b}'\mathbf{Z}_i) \tag{12}$$

where Φ is the standard normal CDF and the μ_s are unknown thresholds to be estimated along with the coefficients $\mathbf{b}'$. The thresholds, μ_j, are important in that they map the observed discrete indicator of women's power λ_i on to underlying continuous empowerment λ_i^*. Specifically, in our context the μ_j, $j = 0...3$ break up the underlying continuous range of women's empowerment into four segments that are identified with the observed levels of empowerment. We impose the standard normalizations that $\mu_{-1} = -\infty$, $\mu_0 = 0$, $\mu_3 = \infty$, and assume that $\mu_{j+1} > \mu_j$.[3] We estimate equations 1 and 2 jointly under the assumption the errors $\varepsilon_i^v$and ε_i^λ follow a standard bivariate normal distribution. We assume a recursive structure whereby no feedback effects occur on women's empowerment due to adoption. Common unobserved effects on adoption

[3] We note that the normalization of the first threshold to zero (and estimating only the remaining two thresholds in our case) is interchangeable with suppressing the constant term in equation 2 and estimating the first threshold. With our normalization, the negative of the estimate of the constant term can be interpreted as the first threshold , and the remaining thresholds can be defined relative to the first.

and empowerment are controlled for using ρ, the correlation between errors terms $\varepsilon_i^v$and ε_i^λ:

$$\varepsilon_i^v = \rho(\gamma_i)\theta_i + \xi_i^v \tag{13}$$

$$\varepsilon_i^\lambda = \theta_i + \xi_i^\lambda \tag{14}$$

where θ_i is a household specific unobserved factor, ρ is the correlation between the errors terms computed using the coefficient on the unobserved heterogeneity term, γ_i, and the ξ_i^k are pure random errors. That is, ρ captures the effect of unobserved factors such as shocks to household income or measurement errors in the two variables that may simultaneously change both empowerment and adoption.

Table 1 reports predicted signs, descriptive statistics and definitions of all variables used in our analysis. Based on our conceptual model (and equation 9 of our empirical framework) we include a measure of empowerment in the adoption equation. To identify the effect of empowerment on adoption, we include in $\mathbf{X_i}$ the main drivers of adoption identified in the MCS adoption literature (see review Lewis). These variables include household wealth, household education, age of the head, a dummy for female head, and household composition variables (household size and the ratio of the number of children to adults). We account for the effect of access to credit on adoption using a dummy for the presence of a bank within the village. To control for shifts in adoption patterns due the potentially weaker access of minorities to stove dissemination and informational programs, we include a dummy variable for high caste status of a household. Finally, we include measures of household's electricity access, the remoteness of the village in which a household is located, and, in some, specifications we include a series of regional dummies (North, South, East, West, North-East*)* to capture broader regional differences in adoption patterns relative to the central (base category) region. In addition to the standard determinants, we also introduce three new control variables that are likely to affect adoption. These include an information variable indicating women's exposure to public media such as TV and radio, a social network variable indicating if the household has personal relations with a medical doctor and a labor market variable indicating the presence of the Sampoorna Gramin Rozgar Yojana (SGRY) wage earning program in the household' village.

Our specification of $\mathbf{Z}_i$ focuses on distribution factors or variables that affect the intra-household distribution of power but not preferences directly. To this end we include four different variables: the education difference between the most educated male and female in the household, the economic status of a woman's

birth or natal family relative to her husband's at the time of her marriage, the percentage of women in the household who participate in the labor market, and whether the woman is a legal owner of the residence (cite chiappori etc). We also include a community level variable indicating the presence of a women's self-help organization, Mahila Manda, in the village. In addition to the above distribution variables we also include in Z_{it} variables that are common to X_{it} and are expected to affect empowerment. These variables include the the age of the household head, women's information through public media, female headship, caste, remoteness of village and households' access to wage employment programs.

The joint estimation approach yields estimates of the coefficients of the individual determinants of adoption including the effect of empowerment which we use to test our main hypothesis. For a variable that appears in both the adoption and the empowerment equation, the model estimates the direct effect of the variable on adoption as well as its indirect effect through its influence on empowerment which, in turn, affects adoption (greene gender). Additionally, conditioning on the error correlation allows us to disentangle causal from common unobserved heterogeneity effects of empowerment and adoption.

Results The descriptive statistics in Table 2 show that in our sample of 25,427 households, drawn from 1445 villages and 6 aggregate regions from rural India, a typical household has about five members and is headed by a male around 47 years of age. The maximum education level of a household member is about 6 years. In about 50 percent of the households, women access information through TV and radio newscasts and about 22 percent of the households have access to a medical doctor within their social network. The typical household receives about 10 hours of electricity service a day, although there is large variance in service across households. Female headed households constitute only a small fraction of the sample (0.1 percent), possibly because in rural India widowed or divorced women's households are typically absorbed into family networks and become part of a male headed household.

The descriptive results also show considerable heterogeneity in distribution factors across households. The average education gap between male and female household members is about 3 years with wide variation around the mean gap across households. On average 40 percent of women in a household work outside the home in formal and informal jobs. For a small proportion of households (14 percent), a married woman in the household perceived her birth family to be of a higher economic status than her husband's family, and in

an even smaller proportion of households (12 percent) a married woman was a legal owner of the household's residence. The women's empowerment indicator which takes values between 0-3 also suggests the lack of women's empowerment, relative to men, in rural areas of the country. On average women are not primary decision makers in the household with regard to the purchase of household appliances.

Table 2a and 2b report the findings of the FIML estimates of joint model for adoption and empowerment. The adoption parameters appear in table 2a and the empowerment parameters in 2b. We present the results of 4 different specifications of the joint model: Model 1 contains only distribution factors in the bargaining equation that are assumed to not affect adoption; Model 2 extends the set of explanatory variables in the empowerment equation to include common variables that also affect adoption; Models 3 and 4 include regional control variables in adoption and in both equations, respectively.

The coefficient of empowerment is positive and highly significant across the four different specifications (table 2a row 2). This finding provides strong evidence that when women have high empowerment in the household the probability of MCS adoption is higher, relative to the case when men have high empowerment. The finding is consistent with our theoretical prediction about the positive influence of empowerment on adoption. It also consistent with a non-zero differential in women's preferences for MCS technology relative to men.

Consistent with the previous empirical literature on MCS adoption we find highly significant positive effects of household wealth and education on adoption. The findings are also robust across the different specifications. Controlling for household wealth and education, we find no significant effect of the age of the head on adoption. However, we find a significant negative effect of the household head's age on adoption indirectly through its effect on women's empowerment. In households with older heads, women's empowerment is significantly lower, which, in turn, has adverse effects on adoption. This can be seen in models 2-4 where the age variable is included as a covariate in the empowerment equation (table 2b row 7).

According to the current MCS literature, female headed households are expected to have a higher probability of adoption since women disproportionately bear the brunt of indoor air pollution in developing countries. However, some scholars argue against this view since female headed households are relatively poorer and, hence, are less able to afford the start-up cost of new stoves or electricity connections (Kohlin

eta al.,). According to Kohlim etal., conditional on household wealth, and the fact that female headed households are more able to express their higher preferences MCSs due to their higher empowerment, they may be at a disadvantage in dealing with the transaction costs associated with adoption. Our findings are consistent with latter view. We find a direct negative effect of female headship on adoption (table 2a row 6) and an indirect positive effect on adoption due to the fact that women in female headed households have higher empowerment (table 2b row 9) which as noted earlier increases the probability of adoption.

We find that household size has a negative effect on adoption. This may reflect the fact that the attributes of a modern stove may make cooking for large numbers of people more cumbersome, or that the costs of transitioning to a new cooking technology increases with the scale of the household's cooking activity. Access to credit, proxied by the presence of a bank in the village in which a household is located as well access to electricity, consistent with our expectations, have positive and significant effects on adoption.

We do not find statistically significant affects on adoption for households with a larger proportion of children, high caste, those located in relatively more remote locations, those living in villages with additional wage earning programs or where women have greater access to information through radio and TV. However, many of these variables have significant effects on adoption that is mediated through intra-household empowerment of women. Women's exposure to information from public media has a strong and positive effect on women's empowerment - an effect that is robust across all four specifications (table 2b). Our result regarding the empowering effect of mass media lends support to a growing literature on the impacts of television on gender roles and women's empowerment (Barkat (2002) Chong and La Ferrara (2009) Jensen and Oster (2009 ADB (2010). Remoteness has a negative effect on adoption through its indirect negative effect on empowerment. Households living in villages with additional wage earning opportunities lower the empowerment of households, with consequent negative effects on adoption. This finding suggests that the additional wage earning programs, by their very nature (manual labor in hard construction jobs) mostly induce men to self select into the program. If this is the case then our results reflect the consequent decrease in empowerment of females due to lower contributions of women to total household income.

We find the effects of distribution factors on adoption be consistent with theoretical predictions. The male-female education gap has a large negative effect of empowerment of women. Female labor market

participation, birth status and home ownership all have strong positive effects on women's power. These findings are also robust across all specifications. Our results are consistent with a large body of literature which shows that intra-household empowerment matters for household decision-making, In particular Allendorf (2007) finds that when women's participation in the labor market increases their decision making authority within the household. Studies have also shown that women's ownership of property is associated with increased decion-making authority (Swaminathan et al 2012; Park, 2007; Agarwal, 1994; Allendorf, 2007). Surprisingly we don't find a positive effect of women's welfare program in the village on women's intra-household empowerment.

We also find significant regional variation in the mean levels of both empowerment and adoption. The statistically significant correlation between the error terms in models 1 and 2 suggest the presence of unobserved household heterogeneity that affect both empowerment and adoption. The statistically significant empowerment coefficient in these models suggests that empowerment has a positive effect on adoption even after accounting for common influences that move both variables. The correlation between the equations, however is broken once regional controls are introduced.

5.2 A stochastic threshold model of empowerment

Consider the women's empowerment in equation 10, and its empirical counterpart in equation 11. In this section we focus on a parsimonious specification of 11, in which the only explanatory variables are the standard intra-household distribution factors discussed in the literature. The left hand side of equation 10 is the underlying continuous level of empowerment λ_i^*. The left hand side of equation 11 is the reported level of power, λ_i; respondents were asked to rank the power of women in their households on a four-point ordered scale. If there existed a universally accepted, "objective" scale along which to measure womens' empowerment, then we could be confident that our households' responses would "correctly" reflect women's true empowerment status. In the absence of such a scale, individuals from different cultures, ethinicity and socio-economic status might assign different meanings to each of the four points on the scale that we provided to them. In this case, a potential problem would arise: there might be systematic differences across households or subgroups of households in the mapping from the true but unobserved levels of women's

empowerment to our discrete scale.

This issue related to the mapping from unobserved to observed scales is not unique to our problem. It arises whenever the outcome variable is one for which an objective measure is not available. For example, if we are studying child growth rate, and the survey question was: "how many inches did your baby grow in the last month?" the subjective component would be relatively low, since inches are inches, notwithstanding measurement errors. On the other hand, if the question were "do you like your indian food mild, median, spicy, hot?" both components would play a role. Indeed one could imagine administering the survey in Delhi and Des Moines, and finding that people in Des Moines liked hotter Indian food than those in Delhi. This would almost certainly be attributable to the fact that "hot" means something much less hot in Des Moines than Delhi. A prominent example is from the health literature where people asked to rank their own health on an ordered scale respond differently not only because their true underlying health status differs but also because they subjectively interpret the different points on the scale (see e.g., Sen A. 2002).

This problem has two consequences for our preliminary finding that women's empowerment has an effect on a household's MCS adoption decision. First, if the mapping between observed and unobserved empowerment differs systematically across households with different cultures and ethinicity, then, even though empowerment does in fact have an impact on adoption, women may not be able to influence the adoption decision through bargaining. Consequently, our regression results might conclude that there is a limited role for government polices that seek to increase adoption by empowering women, but in fact the conclusion is based on not taking into account the threshold effects.

Second, if the mapping between observed and unobserved empowerment differs systematically across households due to pure reporting errors, for example, based on the characteristics of individual respondents, then the coefficient on empowerment in the previous section is inconsistent. Thus, it is important to examine if the intra-houshold distribution factors retain their expected signs and statistical signifcance after controlling for unobservd heterogeneity that may distort the mapping between the observed and unobserved empowerment scales. If they do, then we can be more confident that bargaining power matters in adoption decisions *and* women can influence adoption through negotiation.

Accounting for cross-sectional differences in the mapping from unobserved to observed empowerment

scales, the estimated coefficients on the intra-household distribution factors (e.g., education differences) can be expressed as a composite of two effects: a) an objective effect which would show up on a common objective scale of women's empowerment, and that would reflect the extent to which women can influence the MCS adoption decision through bargaining and negotiation, and b) a subjective effect, unrelated to the effect of the distribution factor, which would reflect differences in the household or the respondents' interpretation of the concept of women's empowerment. To the extent that such interpretations vary by cultural and socioeconomic characteristics of households, the subjective effect would embody "policy exogeneous" social norms of different subgroups which makes them interpret empowerment status differently.

We incorporate cross-sectional differences in mapping of observed and unobserved empowerment scales by allowing the thresholds of the ordered probit in equation (11) to vary across individuals (see Maddala 1983; Terza 1985). Since it is difficult to define a full set of threshold covariates based on observed variables alone, we allow the thresholds to be stochastic (see Weterings, Harris, and Hollingsworth, 2012).

We specify four sources of threshold heterogeneity. First, we allow each distribution factor included on the right hand side of 11 to have an effect through the threshold, in addition to their effect on underlying empowerment. For instance, households in which women are less educated than men may be less likely to fall into the high empowerment category (that women are sole decision-makers) on an objective scale due to women's lower education levels. They may also have a lower threshold for what the high empowerment category represents, relative to households where women are more educated. Second, we allow observed cultural and ethnic chracterisctics to affect the thresholds. We include two observed sources of such variation - caste and female headedship. Third, since villages are relatively homogeneous units where people with common social values agglomerate or have lived for generations, social and cultural norms are likely to vary more across villages relative to within villages. We exploit this heterogeneity as a source of threshold shift by incorporating village level random effects as threshold covariates. We expect that the random effects will sweep all differences in scale that vary across villages. Finally, we account for the the characteristics of actual respondent who answered the empowerment question since these characteristics are likely to condition their interpretation of the power scale. For example, older or more educated female respondents may have a higher threshold for the high women's power category and, thus, underreport on that category relative to younger

respondents. We include three respondents characteristics - the age and education of the respondent, the number of children she has and whether a non-houhehold member was present during the interview.

Following Greene and Hensher (2010), our stochastic threshold model for women's empowerment is obtained by specifying the thresholds in equation 11 as:

$$\mu_{ij} = \mu_{ij-1} + e^{(a_{0j} + \mathbf{a}_1' \mathbf{w}_i + a_{2j}\Omega_v)},\ j = 1, 2 \tag{15}$$

where the a_{0j} denote the constant terms in each threshold μ_j, $j = 1, 2$; $\mathbf{a}_1'$ denotes the effect of a vector of observed determinants,$\mathbf{w}_i$, on the thresholds, and a_{2j} denotes the standard deviation coefficients on the unobserved village random effects Ω_v, which are assumed to be $i.i.d$ normal. As before, we use the normalizations $\mu_{-1} = -\infty$, $\mu_0 = 0$, $\mu_3 = \infty$. The specification above allows covariates to nonlinearly affect the spacing between thresholds rather than their absolute levels. Note that our constant threshold specification (model 1) in the previous section is nested within the model above and is obtained when a_1 and a_2 are both zero. The model is estimated after integrating out the random effects using a simulated maximum likelihood procedure (Greene 2010; Eluru, Bhat, and Hensher 2008; Cunha and Navarro 2007).

5.2.1 Results

Table 3 presents the results for the stochastic threshold ordered probit model. Controlling for subjective effects, we find that the male-female education gap has a negative and statistically significant effect on probability that women are sole decision makers. Similarly, women's labor market particpation, their higher birth family status relative to their husband's and their property ownership all have significant and positive effects on underlying empowerment. These results support are earlier findings and provide evidence that the distribution factors, on an objective scale, impact empowerment in the direction predicted by theory. Since the distribution factors operate at the household level and within clearly defined variables such as education, polices can target these variables (or other distribution factors that increase women's bargaining position) to increase women's bargaining power and increase outcomes for which women have differential preferences relative to men, and in particular, affect the adoption of MCSs. Interestingly, relative to the fixed threshold model (model 1) in the previous section, the magnitude of the eduation gap coefficient is smaller, while the magnitudes of the rest of the distribution factors are larger in table 3.

The large number of significant threshold explanatory variables in table 3 indicates that the threshold model holds constant more heterogeneity across housholds, relative to model 1. The statistically significant standard deviations, along with the mean, on the the village random effects suggest that there is considerable unobserved heterogeneity due to the influence of cultural and social factors on women's empowerment. In addition to the objective effect of the education gap on women's empowerment, we find that in households where women are relatively less educated the thresholds are scaled back. This is evident from the negative and statistically significant coefficient on the male-female education gap variable in the threshold specification. For example, these housholds, relative to others, are more likely to report that women are the sole decision-makers. The subjective effect of housholds with greater particpation of women in the labor market, with women from birth families that are well off, and those in which women own property work in the opposite direction. The thresholds for these housholds are scaled up which implies that they have a stricter definition of women's power and are thus less likely to report that women are the sole decision makers. Female headed housholds have a lower threshold for what constitutes high empowerment. Interestingly, we find that households from higher castes have a higher threshold for the power categories. Thus high caste households are less likely to report that women have power.

We also find that the characteristics of the respondent (who is always a women by survey design) to the interview questions matter and, therefore, controlling for them is important for obtaining consistent estimates of objective effects. If the respondent is older she has a more stringent definition of power and hence higher thresholds on the power scale. Surprisingly, the thresholds are scaled down for respondents with a larger number of children. The respondents education and whether or not an outsider (not a member of the household) was present during the interview had no effect on the thresholds.

6 Conclusions

We examine the barriers to the adoption of modern cook stoves in rural India. Using a collective household model we derive testable hypotheses regarding the role of women's power and their differential preferences for MCSs. Our econometric results drawn from a probit- ordered probit model shows that women's empowerment significantly increases households' MCS adoption. Using a stochastic threshold model we further

examine the source of the empowerment effect on adoption. Given that women value ICSs more than men, women's empowerment can increase ICS adoption. However, it is important to distinguish between alternative hypotheses regarding the source of women's empowerment. If women's empowerment is due to their bargaining & negotiation skills, then ICS programs can increase adoption by marketing stoves in a way that empower women. An example is a MCS purchase subsidy directed at women which would improve women's bargaining positions. If instead women's power is given "exogeneously" by social, cultural or other sources then MCS programs will have limited success by targeting women. More profound changes of social norms would be required to mobilize women's greater preferences. We show that although cultural influences are substantial, the empower effect on housholds' MCS adoption is driven significantly by women's bargaining power. MCS polices should therefore target women and examine ways of marketing stoves that exploit women's higher preferences by empowering them.

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Table 1. Variable Definitions, Descriptive Statistics and Predicted Signs

	Mean	Std. dev	Predicted Sign (Adoption)	Predicted Sign (Empowerment)	Variable Description
Women's Empowerment	0.74	0.77			Ordered variable;3= women decide alone; 2= women decide but consult the men;1=.men decide but consult women; 0= men decide alone
Household Wealth	9.80	5.21	+		Index of houshehold wealth
Household education	6.27	4.90	+		Highest education level achieved by a household adult (21+) member
Age of head	47.61	13.70	+/-		Age in years
Female head	0.10	0.30	+/-		Dummy variable; 1 if head is female
Household size	5.39	2.65	+/-		# of household members
Child/adult ratio	0.27	0.22	+		Proportion of individuals in household younger than 14 years of age
Bank in village	0.29	0.45	+		Dummy variable; 1 if village has a bank
High caste	0.19	0.39	+		Dummy variable; 1 if high caste
Hours with electricity	9.95	8.70	+		Hours in a day with electricity service in household
Dist. To district HQ.	44.62	27.24	-		Distance of village from district headquarters
Wage Emp. Program in Vlg.	0.43	0.49	+		Dummy variable; 1 if employment program in village
Medical network	0.22	0.42	+		Dummy variable; 1 if household's social network includes a medical doctor
Female media exposure	0.51	0.50	+		Dummy variable; 1 if women in household exposed to TV and radio
MF Education difference	2.44	4.65		-	Education difference between most educated male and most educated female
Female lbr. mkt. participation	0.39	0.27		+	Proportion of women in household employed outside home
Female birth family status	0.14	0.35		+	Dummy variable; 1 if women perceived natal family as higher economic status than husband's family during time of marriage
Female home ownership	0.12	0.32		+	Dummy variable; 1 if woman's name is on legal papers of the house
Women's welfare program	0.48	0.50		+	Dummy variable; 1 if village has a Mahila Mandal
North	0.29	0.45	+/-	+/-	Dummy variable; 1 if a Northern State
South	0.19	0.40	+/-	+/-	Dummy variable; 1 if a Southern State
East	0.24	0.42	+/-	+/-	Dummy variable; 1 if a Eastern State
West	0.10	0.30	+/-	+/-	Dummy variable; 1 if a Western State
North-East	0.13	0.34	+/-	+/-	Dummy variable; 1 if a Nort-eastern State, (base=central)
Sample Size (# households)	25,427				

Table 2A. Adoption: Probit – Ordered Probit system. Joint FIML Estimates

	MCS Adoption Equation							
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	*Std. error*	*Coeff.*	*Std. error*	*Coeff.*	*Std. error*	*Coeff.*	*Std. error*
Constant	-2.375***	0.072	-2.434***	0.087	-2.188***	0.108	-2.175***	0.103
Women's Empowerment	.15084***	0.049	.15659***	0.051	.11435**	0.053	.11162**	0.053
Household wealth	.09391***	0.003	.09405***	0.003	.10450***	0.003	.10450***	0.003
Household education	.01346***	0.003	.01321***	0.003	.00963***	0.003	.00964***	0.003
Age of head	0.00054	0.001	0.00169	0.001	0.0012	0.001	0.00117	0.001
Female head	-.07088*	0.042	-.11536**	0.050	-.09243*	0.051	-.09101*	0.051
Household size	-.0343***	0.005	-.03424***	0.005	-.03010***	0.005	-.03010***	0.005
Child/adult ratio	-0.00605	0.065	-0.0046	0.065	0.01983	0.065	0.01962	0.065
Bank in village	.15842***	0.024	.15853***	0.024	.16872***	0.025	.16854***	0.025
High caste	0.03004	0.030	0.03102	0.030	0.04321	0.031	0.04355	0.031
Hours with Electricity	.00320**	0.002	.00321**	0.002	0.00068	0.002	0.00068	0.002
Distance to District HQ	-0.00023	0.000	-.49920D-04	0.000	-0.0004	0.000	-0.0004	0.000
Wage Emp. Program in Vlg.	0.02095	0.023	0.02559	0.024	0.00598	0.025	0.00522	0.025
Medical Network	.07286***	0.026	.07272***	0.026	.08119***	0.027	.08110***	0.027
Female exposure to media	0.04289	0.027	0.03218	0.027	-0.005	0.028	-0.0052	0.028
North					-.24852***	0.061	-.25962***	0.062
South					-.60712***	0.067	-.61954***	0.067
East					-.19365***	0.061	-.20104***	0.061
West					-.15628**	0.066	-.16527**	0.066
North-east (base=central)					-.22861***	0.065	-.23677***	0.065

Table 2B. Empowerment: Probit – Ordered Probit system. Joint FIML Estimates

	Women's Empowerment Equation							
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	*Std. error*	*Coeff.*	*Std. error*	*Coeff.*	*Std. error*	*Coeff.*	*Std. error*
Constant	.16752***	0.012	.95436***	0.032	.95398***	0.032	.69377***	0.044
Education difference	-.01633***	0.002	-.00645***	0.002	-.00638***	0.002	-.00794***	0.002
Female lbr. mkt. participation	.00054***	.3548D-04	.00064***	.3911D-04	.00064***	.3918D-04	.00064***	.3919D-04
Female birth family status	.31940***	0.021	.29698***	0.021	.29750***	0.021	.29618***	0.021
Female home ownership	.64154***	0.024	.58711***	0.025	.58707***	0.026	.59437***	0.026
Women's welfare program			-0.0131	0.015	-0.0134	0.015	0.02091	0.016
Age of head			-.01685***	0.001	-.01684***	0.001	-.01691***	0.001
Female exposure to media			.16013***	0.015	.16017***	0.015	.17003***	0.015
Female head			.66510***	0.021	.66584***	0.021	.66404***	0.021
High caste			-0.0122	0.020	-0.0122	0.020	-0.0198	0.020
Distance to District HQ			-.00255***	0.000	-.00255***	0.000	-.00222***	0.000
Wage employment program			-.06965***	0.015	-.06957***	0.015	-.05783***	0.015
North							.27805***	0.035
South							.30207***	0.041
East							.17517***	0.036
West							.21862***	0.038
North-east (base=central)							.19127***	0.040
Threshold 1 (μ_1)	1.49998***	0.012	1.55869***	0.012	1.55872***	0.012	1.55995***	0.012
Threshold 2 (μ_2)	1.89672***	0.015	1.99213***	0.016	1.99229***	0.016	1.99258***	0.017
Correlation of errors	-.09001**	0.043	-.09258**	0.044	-0.0582	0.046	-0.0557	0.045

Table 3. Empowerment: Stochastic Threshold Model. Simulated MLE Estimates

	Coefficient	Std. Error
Women's Empowerment Equation		
Constant	.14174***	0.006
Education difference	-.00569***	0.001
Female labor mkt. participation	.00071***	.0004
Female birth family status	.36186***	0.018
Female home ownership	.83864***	0.020
Intercepts of random thresholds μ_1 and μ_2 (a_{0j})		
a_{01}	.60806***	0.035
a_{02}	-.48413***	0.048
Standard deviations of random thresholds (a_{2j})		
a_{31}	.40996***	0.013
a_{32}	.61320***	0.051
Threshold covariates ($\boldsymbol{a_1}$')		
Education difference	-.00401**	0.001
Female labor mkt. participation	.00033***	0.0001
Female birth family status	.04266**	0.110
Female home ownership	.34767***	0.019
Female head	-.97328***	0.069
High caste	.03708*	0.019
Non-household member presence	0.0143	0.031
Respondent age	.00417***	0.0008
Respondent Education	-0.0018	0.002
Respondent # Children	-.04043***	0.005