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Intra-household bargaining over household technology adoption

Sandeep Mohapatra[1] · **Leo Simon**[2]

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Abstract We examine the barriers to adoption of improved cook stoves (ICSs) in rural India, using a large, nationally representative dataset. We develop a collective household model to derive testable hypotheses about whether women's intra-household influence, together with their relatively strong marginal preference for ICSs, affects adoption. Using a joint adoption-influence econometric model, we find compelling evidence that women's influence over intra-household decisions significantly increases adoption. We further distinguish between alternative sources of women's influence, and argue that our distinction has potential implications for ICS dissemination policies. We find that while there is significant variation in women's influence across rural India due to cultural and other sociological factors, the effect of intra-household influence on adoption has a significant bargaining power component. Our results suggest that ICS programs may be able to increase adoption by marketing stoves in ways that empower women.

Keywords Bargaining power · Gender · Health · Development · Collective household model · Stochastic threshold ordered probit

JEL Classification D1 · I1 · 01

✉ Sandeep Mohapatra
smohapat@ualberta.ca

Leo Simon
leosimon@berkeley.edu

[1] University of Alberta, Edmonton, Canada

[2] University of California, Berkeley, Berkeley, CA, USA

1 Introduction

According to Martin et al. (2011), pollution from burning biomass using traditional household cooking technologies is the leading environmental cause of death in developing countries. Over 2.5 billion people in developing countries use biomass (viz., fuelwood, charcoal, crop residue, dung and coal) as their main cooking fuel. In Sub Saharan Africa almost 76 % of the population are reliant on biomass. India dominates the global pattern of biomass use in absolute terms, with almost 740 million people, comprising of 70 % of the population of the country, using biomass as their primary energy source for cooking and heating (WHO 2009a).

Traditional cooking technologies used by households to process biomass into energy are often inefficient, produce large amounts of smoke and respirable particulate matter, and are associated with significant health risks.[1] Biomass smoke from the use of traditional cooking technologies is responsible for an estimated 1.5 million deaths, annually (WHO 2009b), claiming more lives every year than malaria. 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. In particular, almost half of the mortalities due to biomass burning are among children under age five and 60 % of the adult mortalities consist of women (Bruce et al. 2002).

Improved cookstoves (ICS),[2] which use a modern technology to deliver higher efficiency and lower smoke emissions, are capable of dramatically reducing the health risks (Smith et al. 2011). While there is now substantial evidence that women are disproportionately affected by the adverse effects of traditional cooking technologies relative to men, their role in the relevant household technology choice—whether or not to use a traditional stove—is still not well understood. It is becoming increasingly important to understand the linkage between gender and technology purchasing decisions, since ICS adoption rates in developing countries remain very low despite the recognized benefits for indoor air pollution, health of women/children and fuel collection times, and years of stove dissemination programs and global attention paid to the issue. To the extent that women assign higher values to ICSs 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 ICS adoption would be more successful if they marketed and disseminated stoves in a way that, as a byproduct, also contributed to the influence of women over household purchases.

The overall goal of this study is to examine the effect of a woman's role in—or influence over—household economic decisions about household energy technology choice. We develop a conceptual model of intra-household decision-making based on a collective household model which relates ICS adoption to bargaining among male and female members of the household. Our model departs from the standard

[1] Traditional technologies refer to open fires and cookstoves without ventilation chimneys.

[2] Biomass fuelled stoves that are equipped with ventilation chimneys.

collective decision-making framework (e.g., Browning and Chiappori 1998) in that we distinguish between the extent to which women influence household decisions and two distinct determinants of women's power. In the literature these three concepts are usually bundled into a single parameter and called "bargaining power." We argue in this paper that the distinctions we identify have important implications for the design of policies whose goal is to increase ICS adoption.

We empirically examine the role of women in intra-household decision making regarding ICS adoption, using a nationally representative dataset collected in 2005–2006, with information on stove use 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. The data are drawn from the India Human Development Survey (Desai et al. 2008). 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 household technology adoption. We construct a proxy for women's role in household decision making, using information on male versus female involvement in the purchase of household appliances. Our role/influence 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. This approach 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 women's role in household decision making. Our work contributes to the recent literature on energy–gender interactions which finds characteristics of female household members to be significant in regression models of ICS adoption in societies where decision making is male dominated (El Tayeb Muneer and Mukhtar Mohamed 2003), and that women have higher preferences than men for ICSs, but lack decision-making authority over stove purchases (Miller and Mobarak 2011).

To meet our overall goal, we have two specific objectives. First, we seek to estimate the effect of women's intra-household on households' cooking technology choice. The implication of a positive and significant effect of women's influence on adoption is that, given women's higher preferences for ICSs than men, an increase in their influence may increase ICS adoption. Our second objective is to distinguish between alternative hypotheses about the sources of womens' influence. If the extent of a women's influence is dependent on her bargaining and negotiation skills, ICS programs can increase adoption by increasing women's bargaining power. If, instead, women's intra-household role is bestowed on them "exogeneously," by relatively immutable social, cultural or other drivers, ICS programs will have limited success by targeting women.

Our study makes two novel contributions. The first contribution is applied econometric. In studies of the effects of intra-household bargaining power on household adoption, the standard approach is to include a gender-specific variable related to women's bargaining power, directly as a covariate in the adoption equation (e.g., El Tayeb Muneer and Mukhtar Mohamed 2003). However, identification of the effect of the woman's intra-household role within this framework is problematic for two reasons. First, unobservables are likely to affect both adoption and women's influence, making it difficult to identify the causal effect of women's influence on adoption. In some applications, for example, when both adoption and influence are measured continuously, the endogeneity can be addressed either with instrumental variable methods, or by using Heckman's approach when influence is measured as a dummy variable and is endogenous (Heckman 1978).[3] But our particular formulation specifies a binary outcome (adoption) as a function of a discrete endogeneous covariate (influence). We overcome the endogeneity problem by separating the estimation of the adoption and women's influence parameters, and jointly estimating a probit adoption model and an ordered probit influence model. A second problem with the standard framework is that it does not account for indirect effects of observed covariates, such as wealth or household head's age, on adoption. For instance, female headed households have been argued to be both less likely to adopt ICSs because they are less able to deal with the transactions costs of new connections or pay upfront fixed costs—a direct effect—and more likely to adopt because they are characterized by greater women's influence—an indirect effect. The true effect of a covariate on adoption, thus, can be gauged only by separating out the direct and indirect effects. We accomplish this by introducing common covariates into our joint model of adoption and influence.

The second contribution of our study relates to modeling. We draw a novel distinction between the *role* that women play in relation to household decisions and whether or not they have *bargaining power* with respect to these decisions. In essence, we address, in the context of ICS adoption, the question: "do women have a role in the adoption decision?" This question is conceptually distinct from the related one: "do women have a role in the adoption decision *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 very large, or a very small, role in a particular decision, but in either case, the magnitude of her role is determined by factors, such as societal norms and cultural traditions, over which the individual woman has absolutely no control. 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 her household, such as differences in skill or education levels.

The two possibilities have quite different policy implications. If women care more about clean stoves but the extent of their role in household decision-making is "exogenously" bestowed upon them, then women's differential role in the allocation of resources to ICSs 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

[3] The discussion surrounding the Heckman (1978) model refers to Heckman's work on dummy endogenous variables in a simultaneous equation system, and not the Heckman selection model.

social norms would be required to mobilize women's differential preferences for ICSs. If on the other hand, the extent of a woman's role is limited only by her bargaining power, and that can be changed by policy, then interventions can potentially increase adoption by empowering women.

Our paper also makes a novel contribution to the empirical bargaining literature, which does not distinguish between these two alternative hypotheses about the source of women's intra-household 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 a particular application. Thus, to meet our second objective and distinguish between alternative sources of women's intra-household role or influence, we first estimate the effects of women's role in household decision making using the joint probit–ordered probit model. We then examine the intra-household role equation using a stochastic threshold ordered probit model which, in contrast to the standard ordered probit, relaxes the assumption that the same process determines women's role in all households regardless of their cultural and social characteristics. This approach allows us to separate out out the two components of influence.

Surprisingly few studies have examined the barriers to households' adoption of ICSs in developing countries. In a recent review, Lewis and Pattanayak (2012) argue that the ICS adoption literature is "thin" 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. Most of the studies of ICS adoption emphasize the importance of factors such as household wealth and education of household members as determinants of adoption, while key contextual drivers such as adoption barriers faced by women are ignored (Kohlin et al. 2011).

Consistent with the standard technology adoption literature, studies such as Fuglie and Kascak (2001), Barnes et al. (1994) and Amacher et al. (1992) show that household wealth is a primary determinant of ICS adoption. Relatedly, Edwards and 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 explanatory variables, since higher education and experience enable consumers to interpret information and value the benefits of an improved technology (Slaski and Thurber 2009; Shanko et al. 2009). According to Beyene and Koch (2013) households with female heads and those with a larger proportion of children are more likely to adopt ICSs, relative to either male-headed households or households without children, since the adverse consequences of biomass stoves are particularly acute for women and children. Gebreegziabher et al. (2012) show that after accounting for income, education, age and occupation of the household head, larger households are more likely to adopt. Caste and religious affiliations of households also can affect ICS adoption due to differentials in the diffusion of information and access to dissemination programs among minorities. A recent study by 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 randomized control trial involving two districts in Bangladeshi villages, found that women have a higher preference for improved stoves. The authors conclude from this that policies will be able to exploit women's higher preferences for ICSs with social change that empowers women.

We control for the determinants identified in the literature and pay special attention to incorporating and isolating the role of a specific contextual factor—women's influence over the adoption decision. India provides a natural context for our study. Over 72 % of the population still lives in rural areas. In rural India, more than 90 % of households use biomass fuels such as dung, firewood, coal and crop residue for household energy needs (Register General 2001). Indoor air pollution from households' biomass accounts for 4–6 % of the national burden of disease and an estimated 500,000 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 ICS technologies into households. Despite these efforts, ICS adoption rates remain very low (under 4 %) in India (e.g., Balakrishnan et al. 2002).

2 Conceptual model

We consider a household with two decision-makers, a man (*m*) and a woman (*f*). We assume for simplicity that there are just two goods; one is a consumption good, the other is an environmental good. The consumption good, which we treat as the numeraire, is denoted by q. The environmental good is indoor air quality, a, or, equivalently, the absence of indoor air pollution, s (for 'smoke'), which generates disutility for both agents. We let $\overline{a}$ denote the level of air quality that would be attained if smoke were reduced to zero, so that $a = \overline{a} - s$. Men and women are assumed to have different preferences over the two goods, since fuel collection costs associated with the production of, and exposure rates to, smoke differ significantly between men and women. For $g = m, f$, let $u_i^g(q, a)$ denote the utility function of the household member with gender g in the ith household. Our assumptions on utility are standard, i.e.,

$$\begin{aligned} &\text{For} \quad g = m,f \quad \text{and} \quad j = q, a, \quad u_{i,j}^g > 0, u_{i,jj}^g < 0; \\ &u_{i,qa}^g > 0; \quad \lim_{q \searrow 0} u_{i,q}^g(q,a) = \infty; \quad \lim_{a \searrow 0} u_{i,a}^g(q,a) = \infty \end{aligned} \tag{1}$$

where $u_{i,j}^g$ (resp. $u_{i,jk}^g$) denote the partial (resp. cross-partial) derivative of u_i^g with respect to good j (resp. goods j, k). The limit properties we impose on the $u_{i,j}^g$'s will ensure that at the solution to the household's optimization problem, positive quantities of both q and a will be consumed. Note that since $a \equiv \overline{a} - s$, u_i^g is decreasing and convex in smoke. These restrictions on u are analogous to those in Basu (2006), who uses a strictly convex function to depict the disutility that parents incur from child labor. In our context, strict convexity implies that the effect of smoke on household members cumulates over smoke levels—an individual may merely dislike a small amount of smoke while larger amounts may be unbearable.

Household decision-making making is assumed to be cooperative, resulting in 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:

$$U_i = \lambda_i u_i^f(q, a) + (1 - \lambda_i) u_i^m(q, a) \tag{2}$$

where $\lambda_i \in [0, 1]$ denotes the woman's weight in the household utility function, representing how much "say" women have in household decisions. In previous sections, we have referred to this variable either as the woman's "intra-household role" or her "level of influence." For the moment, we will "black-box" this variable, treating it simply as a parameter of our model. Later, we will examine its determinants, and address the question of whether its level can be impacted by public policy.

Normalizing all prices to one, reflecting constant prices across a cross-section of households, the household budget constraint is:

$$q + T(a) = W \tag{3}$$

where W is household wealth, and $T(a)$ is the level of technology required to obtain a household level of air quality equal to a. We assume that the household has access to a continuum of technology options, that are increasingly effective at reducing smoke levels; we further assume there is some threshold level of technology, $\bar{T}$, which corresponds to the purchase of an MCS, while traditional cooking technologies correspond to levels of T below $\bar{T}$. The technology $T(\cdot)$ is assumed to satisfy:

$$\text{For} \quad 0 \leqslant a \leqslant \overline{a}, \quad T'(a) > 0, \quad T''(a) > 0 \quad \text{and} \quad \lim_{a \nearrow \overline{a}} T'(a) = \infty \tag{4}$$

The limit property in (4) states that it is prohibitively expensive to reduce smoke $s \equiv \overline{a} - a$ to zero. Substituting the budget equation (3) into the utility function (2), and using the identity $a \equiv \overline{a} - s$, we eliminate a from the model. Moreover, since the quantity consumed of the numeraire, q, is just $W - T(\overline{a} - s)$, u_i^g can now be replaced by a univariate function, v_i^g, of the level of household smoke. (In our econometric model, there are several more parameters, but since they add nothing to our theoretical analysis, we ignore them in this section.)

$$v_i^g(s; W) = u_i^g(W - T(\overline{a} - s), \overline{a} - s) \tag{5}$$

$$\text{with} \quad v_{i,s}^g(s; W) = u_{i,q}^g(W - T(\overline{a} - s), \overline{a} - s) T'(\overline{a} - s) - u_{i,a}^g(W - T(\overline{a} - s), \overline{a} - s) \tag{6}$$

$$v_{i,ss}^g = \left(u_{i,qq}^g T' - 2u_{i,qa}^g\right) T' - u_{i,q}^g T'' - u_{i,aa}^g < 0 \tag{7}$$

$$\text{Finally,} \quad v_{i,sW}^g = u_{i,qq}^g T' - u_{i,qa}^g < 0 \tag{8}$$

The properties we imposed on u_i^g and T [Eqs. (1), (4) respectively] enable us to sign both (7) and (5) unambiguously. In words, (6) and (7) establish that the derivative of each household member w.r.t. smoke decreases, but at a decreasing rate, from positive to negative infinity, as smoke increases from zero to $\overline{a}$, its maximum level. These properties together imply that each $u^g_{i,s}$ cuts zero exactly once in the interval $(0, \overline{a})$, and from above, ensuring that for each household member, there is a unique level of smoke that maximizes u^g_i. We can now replace the household utility function (2) with its univariate version:

$$V_i = \lambda_i v^f_i(s; W) + (1 - \lambda_i) v^m_i(s; W) \tag{2$'$}$$

The household's task is to maximize (2′) with respect to s. Using the same arguments that we applied to its component parts, V_i also attains a unique maximum at some level $s^* \in (0, \overline{a})$. The first order condition for this problem is

$$\text{FOC}(\lambda, s^*, W) = \lambda_i v^f_{i,s}(s^*; W) + (1 - \lambda_i) v^m_{i,s}(s^*; W) = 0 \tag{9}$$

In words, the FOC is satisfied when the λ_i-weighted average of the man's and the woman's marginal rates of substitution between smoke and private good consumption equals the marginal cost of an additional unit of smoke abatement. (Recall that the marginal cost of the private good is normalized to unity.)

We next construct an expression for the effect of λ (women's influence) on s (smoke). Applying the implicit function theorem to the first order condition (9), evaluated at s^*:

$$\begin{aligned} \frac{ds}{d\lambda} &= -\frac{\frac{d\,\text{FOC}}{d\lambda}}{\frac{d\,\text{FOC}}{ds}} = -\frac{v^f_{i,s}(s^*; W) - v^m_{i,s}(s^*; W)}{\lambda_i v^f_{i,ss}(s^*; W) + (1 - \lambda_i) v^m_{i,ss}(s^*; W)} \\ &:= -\text{DEN}(s^*; \lambda, W)\left(v^f_{i,s}(s^*; W) - v^m_{i,s}(s^*; W)\right) \qquad \text{while} \end{aligned} \tag{10}$$

$$\frac{ds}{dW} = -\frac{\frac{d\,\text{FOC}}{dW}}{\frac{d\,\text{FOC}}{ds}} = -\text{DEN}(s^*; \lambda, W)\left(\lambda_i v^f_{i,sW}(s^*; W) + (1 - \lambda_i) v^m_{i,sW}(s^*; W)\right) \tag{11}$$

The term DEN $(s^*; \lambda, W)$—the reciprocal of the denominator in the line above (10)—reflects the "curvature effects" of a change in women's influence on household smoke levels. From (7), the combined effect is unambiguously negative. Hence $\frac{ds}{d\lambda}$ has the same sign as $(v^f_{i,s}(s^*; W) - v^m_{i,s}(s^*; W))$, which depends on the difference between the woman's and the man's marginal rates of substitution of smoke for the consumption good. In particular, an increase in the woman's influence will reduce the level of smoke iff the level that is individually optimal for the woman is less than the smoke level, s^*, that is optimal for the household collectively, i.e., if $v^f_{i,s}(s^*; W) < 0 < v^m_{i,s}(s^*; W)$. [The second inequality follows from (9).] For a given wedge between the marginal preferences of the two household members, the impact of a unit increase in the woman's influence will be greater, the more concave is either household member's utility function. Next, note from (11), and then (5), that $\frac{ds}{dW}$ is positive: an increase in income will reduce the optimal level of smoke.

Since technology is a univariate function of smoke level, it follows that

$$\frac{dT}{d\lambda} = -T'(\overline{a}-s^*)\frac{ds}{d\lambda}; \tag{12}$$

$$\frac{dT}{dW} = -T'(\overline{a}-s^*)\frac{ds}{dW} \tag{13}$$

Since a decrease in smoke levels requires an increase in the technology level, it follows that $\frac{dT}{d\lambda}$ and $\frac{dT}{dW}$, and $\frac{ds}{d\lambda}$ and $\frac{ds}{dW}$, have opposing signs.

Combining (10) and (11) with (12) and (13), we obtain the differential function (14) below, which is the theoretical analog of our estimated equation (16) in the following section. It relates small changes in household technology purchases to small changes in each of the two parameters of our model

$$\Delta T = \frac{dT}{d\lambda}\Delta\lambda + \frac{dT}{dW}\Delta W \tag{14}$$

We now turn our attention to the determinants of the woman's influence variable, λ_i. In the literature on intra-household decision-making, it is customary to refer to λ_i as "bargaining power."(e.g., Reggio 2011). By contrast, our starting point is that the woman's role in any given household decision has two distinct determinants, and we reserve the word "bargaining power" for just one of these. To model this idea, we now write λ_i as a *function* with two arguments, whereas hitherto we treated λ_i as a parameter: from the perspective of the household, the first argument is "endogenous" (or internally sourced) while the second is "exogenous" (or externally sourced). In symbols,

$$\lambda_i = \Lambda(\chi_i; \chi_k), \tag{15}$$

where $\Lambda \in [0, 1]$ and the derivative of Λ with respect to each of its arguments is positive on [0, 1). The variable χ_i is a proxy for a cluster of variables—woman i's "skills"and other ideosyncratic characteristics relative to the men in her particular household (e.g., her education level relative to these men)—that can potentially affect her intra-household role or influence. We reserve the word *bargaining power* for this term. In the analysis which follows, when we talk of *empowering women*, we mean, specifically, taking steps which will increase the value of the variable χ_i.

χ_k proxies a different set of attributes, which may also affect woman i's role, but are derived from cultural and social norms, rather than varying from household to household. We reserve the word *societally constructed gender norms* for this term. For instance, women from high and low caste households, but with identical χ_i values, may have different levels of influence, which they have simply "inherited" by virtue of their caste memberships.

It seems reasonable to presume that from a policy perspective, the endogenous component of influence, χ_i, is more malleable than the exogenous component, χ_k. That is, we presume that it is easier to design policies that target individual women (e.g., Duflo 2003) than ones that target the behavior patterns—which may have deeply ingrained cultural roots—of an entire caste. In our theoretical model, we impose an extreme version of these presumptions, and treat χ_i as a *variable* and χ_k as a *parameter*. (The semi-colon in (15) highlights this distinction.) In reality, of course, it is an empirical question whether the cluster of attributes represented by χ_i do actually have any impact on woman i's intra-household influence. (We turn to this question in the next section.) This empirical question has an analog in our theoretical framework: we assert that $\Lambda_{\chi_i}(\cdot)$ is nonnegative, but leave open the possibility that the inequality may not be strict. To reflect the potential dependence of λ_i on χ_i, we rewrite (14) as (14′).

$$\Delta T = \frac{dT}{d\lambda}\frac{d\Lambda}{d\chi_i}\Delta\chi_i + \frac{dT}{dW}\Delta W \qquad (14')$$

The policy question we address in this paper is whether policy makers can harness the woman's role in household decision making as a policy instrument to increase MCS adoption. For this instrument to have any leverage, however, it is necessary that policymakers have access to tools that can change λ. As we have discussed earlier (p. 12), T is more likely to be responsive to policy interventions if women's influence is "endogenously" sourced rather than "exogeneously," from societally constructed gender norms. Indeed, in our theoretical model, T will be responsive to policy intervention only if *both* $\frac{dT}{d\lambda}$ and $\frac{d\Lambda}{d\chi_i}$ are positive [see Eq. (14′)]. From (10) and (12), $\frac{dT}{d\lambda}$ will be positive iff women have a higher marginal preference for smoke reduction than men, while $\frac{d\Lambda}{d\chi_i}$ will be positive iff "bargaining power matters," i.e., if bargaining plays a significant role in the household decision-making process. Summarizing the above mathematics in words:

Proposition 1 *Policies that can increase a woman's bargaining power within the household will reduce indoor air pollution if and only if* (*a*) *the woman's preferences for smoke abatement is stronger than the man's and* (*b*) *the woman's role in household decision making is strictly increasing in her bargaining power.*

3 Data

The data for our analysis are drawn from the India Human Development Survey (IHDS), undertaken by the University of Maryland and the National Council of Applied Economic Research (Desai et al. 2008). 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.

Our analysis focuses on rural India. Our sample consists of 25,427 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. 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) cooked with biomass on an open fire. We paired the information on stove ownership with actual biomass and other solid fuel use (charcoal, dung, firewood, crop residue and coal) to separate out households that owned a biomass stove but did not burn biomass. Using this approach, we defined households as adopters of the new technology if they did not own a biomass stove or they owned an improved biomass stove equipped with a chimney (categories a and b). Due to our broader definition of “new technology,” we use the term modern cook stoves (MCSs) rather than ICS.

The survey also directed, to a woman in each household who had been married at least once, detailed questions about gender relations and intra-household power. One question provides information regarding the purchase of household items and the decision making authority of male and female members of the household. Decision making authority was classified into several categories, based on whether the decision was made by males, females or jointly. We use this information to create a proxy for women’s intra-household role, based on their decision making authority regarding purchases of household appliances. We also create an index of wealth, or the long term economic status of a household, based on information on goods and assets the household owned and the quality of housing. To identify the determinants of adoption and intra-household roles, we use information related to each household’s socioeconomic characteristics, such as income, age, education level, gender and occupation of the household head and other members, social networks and access to medical doctors, and community characteristics.

4 Empirical framework

4.1 A joint model of MCS adoption and women’s influence

Our observed indicator of MCS adoption, τ_i, is a binary variable, which takes the value one if household i uses an MCS and zero if it uses a traditional one. The standard approach is to specify the cumulative probability of τ_i, conditional on all explanatory variables—such as household wealth, education, etc.—using a probit model. Accordingly, τ_i is a discretization of a latent continuous variable, $\tilde{\tau}_i$, which represents the level of smoke abatement technology acquired by household i. The variable $\tilde{\tau}_i$ is assumed to be generated by the regression model:

$$\tilde{\tau}_i = \alpha + \beta\lambda_i + \gamma'\mathbf{X_i} + \varepsilon_i^{\tau} \tag{16}$$

where α is an intercept term; and $\mathbf{X_i}$ is a row vector of the determinants of adoption which we describe in detail in the next section, with coeffcient vector γ. Our other explanatory variable is a measure of woman i's intra-household role, λ_i, which is an ordered variable with four levels, that affects adoption through the coefficient β.

The relevance of woman's influence as an explanatory variable in Eq. (16), and hypotheses regarding its impact on the adoption probability, can be established by noting that $\tilde{\tau}_i$, the level of smoke abatement technology, corresponds to $T(\overline{a} - s_i^*)$ in the previous section (12, 14′). Woman i's intra-household influence, λ_i, affects technology choice through its effect on household i's optimal smoke level, a_i^*. The probability of observing an MCS in household i is equal to the probability that $T(a)$ crosses the threshold level, $\bar{T}$, introduced on p. 8. If the level of air quality, $a_i^* = \overline{a} - s_i^*$, demanded by household i is at least as high as $\bar{a} = T^{-1}(\bar{T})$, then a_i^* cannot be achieved using traditional cooking technologies, and the household has to purchase an MCS in order to obtain its desired air quality level. The likelihood of MCS adoption can thus be written as:

$$\mathrm{Prob}(v_i = 1|\lambda_i, \mathbf{X_i}) = \mathrm{Prob}\big(T(\overline{a} - s_i^*) \equiv \tilde{\tau}_i \geq \bar{T}\big) = \Phi(\alpha - \bar{T} + \beta\lambda_i + \gamma'\mathbf{X_i}) \quad (17)$$

where Φ is the standard normal cumulative density function.[4]

In the standard probit model, household i's decision whether or not to purchase an MCS is a stochastic one, depending on the realization of the random variable ϵ_i. That is, the household spins a roulette wheel, and buys or does not buy, depending on where the wheel's pointer stops. Under our alternative, "asymmetric information" interpretation of the ϵ_i's, the household's decision is deterministic; either it makes the purchase or it does not, depending on, among other things, its privately known parameter ϵ_i. From the econometrician's perspective, however, the household's decision must be viewed as random, because the ϵ_i's are unobserved: this "objective" uncertainty in the standard probit model is replaced in ours by "subjective" uncertainty.

4.1.1 Endogeneous intra-household influence

To obtain an consistent estimate of the coefficient, β, on influence in Eq. (17), it is necessary to control for the effect of unobservables that may jointly affect both adoption and influence. Without such controls, the causal effect of women's influence on adoption will be conflated with the effect of the unobservables. Standard methods designed to yield consistent estimates of parameters in the presence of endogeneity cannot be used in our context because of the nonlinear form of Eq. (17). These methods include two-stage instrumental variable techniques which are based on moment conditions derived from linear expectations, variances and covariances (Miranda and Rabe-Hesketh 2006). An alternative approach, that accounts for nonlinearity and is commonly used in the context of discrete choice models, obtains the residuals from a linear regression of influence in the first stage, and adds these residuals as an explanatory variable in the second stage adoption equation (Rivers and Vuong 1988). However, this approach assumes a linear first stage model while our influence measure is an ordered variable.

[4] Alternatively, the RHS of (16) exceeds the LHS whenever $-\varepsilon_i^\tau < \alpha + \beta\lambda_i + \gamma'\mathbf{X_i} - \bar{T}$, an event which occurs with cumulative probability $\Phi(\alpha - \bar{T} + \beta\lambda_i + \gamma'\mathbf{X_i})$.

We account for endogeneity by estimating the influence equation separately, although not independently, from the adoption parameters, using full information maximum likelihood (FIML) (Greene and Hensher 2010; McVicar and McKee 2002). To model the discrete nature of our observed influence variable, λ_i, we use a standard ordered probit specification, which assumes that the observed levels of women's influence—the λ_i's—are linked to an unobserved continuous scale of women's influence, $\widetilde{\lambda}_i$, which is determined by a set of intra-household distribution factors, $\mathbf{Z}_i$:

$$\widetilde{\lambda}_i = \mathbf{b}'\mathbf{Z}_i + \varepsilon_i^{\lambda}, \tag{18}$$

where the $\mathbf{Z}_i$'s include a constant term and the four intra-household distribution factors defined earlier. Assuming that the random disturbance, ε_i^{λ}, has a standard normal distribution, the probability that the woman in household i is observed in power category j is:

$$\text{Prob}(\lambda_i = j) = \Phi\left(\mu_j - \mathbf{b}'\mathbf{Z}_i\right) - \Phi\left(\mu_{j-1} - \mathbf{b}'\mathbf{Z}_i\right) \tag{19}$$

where Φ is the standard normal CDF. The μ_j's are unknown thresholds to be estimated along with the coefficients $\mathbf{b}'$. Specifically, in our context the μ_j, $j = 0\ldots3$, break up the underlying continuous range of women's influence into four segments that are identified with the levels of influence observed on our four-point ordered scale, with the standard normalizations that $\mu_{-1} = -\infty$, $\mu_0 = 0$, $\mu_3 = \infty$, and assuming that $\mu_{j+1} > \mu_j$. The thresholds are a crucial part of the ordered probit model in that they map the observed indicator, λ_i, on to underlying continuous measure $\widetilde{\lambda}_i$. Notice that in the above specification the thresholds are assumed not to vary across households and, therefore, can be thought of as constant terms that are specific to each empowerment category. We relax this assumption in Sect. 4.2.

The adoption and influence equations are estimated jointly under the assumption that the errors of the two equations, ε_i^{τ} and ε_i^{λ}, follow a standard bivariate normal distribution. We assume a recursive structure whereby no feedback effects occur on women's influence due to adoption. We control for common unobserved effects on adoption and influence using ρ, the correlation between errors terms ε_i^{τ} and ε_i^{λ}:

$$\begin{aligned} \varepsilon_i^{\tau} &= \rho(\gamma_i)\theta_i + \xi_i^{\tau} \\ \varepsilon_i^{\lambda} &= \theta_i + \xi_i^{\lambda} \end{aligned}$$

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 for $\ell = \tau, \lambda$, the ξ_i^{ℓ}'s 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 influence and adoption.[5]

[5] The likelhood function for our model is given in the "Appendix".

Table 1 Variable definitions, descriptive statistics and predicted signs

	Mean	SD	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 household 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	+/−		No. 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
District 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

Table 1 continued

	Mean	SD	Predicted sign (adoption)	Predicted sign (empowerment)	Variable description
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 north-eastern state (base = central)
Sample size (no. of households)	25,427				

4.1.2 Specification of the joint adoption-women's influence model

Table 1 reports predicted signs, descriptive statistics and definitions of all variables used in our analysis. Based on our conceptual model we include a measure of woman's influence in the adoption equation. To identify the effect of woman's influence on adoption, we include in $\mathbf{X_i}$ the main drivers of adoption identified in the MCS adoption literature. 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 to the potentially weaker access of minorities to stove dissemination and informational programs, we include a dummy variable for the 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, 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's village.

Our specification of $\mathbf{Z}_i$ focuses on distribution factors or variables that affect the intra-household distribution of power, but do not affect 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

Table 2 Adoption: probit–ordered probit system—joint FIML estimates

	MCS adoption equation							
	Model 1		Model 2		Model 3		Model 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	−2.375***	0.072	−2.434***	0.087	−2.188***	0.108	−2.175***	0.103
Women's empowerment	0.15084***	0.049	0.15659***	0.051	0.11435**	0.053	0.11162**	0.053
Household wealth	0.09391***	0.003	0.09405***	0.003	0.10450***	0.003	0.10450***	0.003
Household education	0.01346***	0.003	0.01321***	0.003	0.00963***	0.003	0.00964***	0.003
Age of head	0.00054	0.001	0.00169	0.001	0.0012	0.001	0.00117	0.001
Female head	−0.07088*	0.042	−0.11536**	0.050	−0.09243*	0.051	−0.09101*	0.051
Household size	−0.0343***	0.005	−0.03424***	0.005	−0.03010***	0.005	−0.03010***	0.005
Child/adult ratio	−0.00605	0.065	−0.0046	0.065	0.01983	0.065	0.01962	0.065
Bank in village	0.15842***	0.024	0.15853***	0.024	0.16872***	0.025	0.16854***	0.025
High caste	0.03004	0.030	0.03102	0.030	0.04321	0.031	0.04355	0.031
Hours with electricity	0.00320**	0.002	0.00321**	0.002	0.00068	0.002	0.00068	0.002
Distance to district HQ	−0.00023	0.000	−0.49920D−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	0.07286***	0.026	0.07272***	0.026	0.08119***	0.027	0.08110***	0.027
Female exposure to media	0.04289	0.027	0.03218	0.027	−0.005	0.028	−0.0052	0.028
North					−0.24852***	0.061	−0.25962***	0.062
South					−0.60712***	0.067	−0.61954***	0.067
East					−0.19365***	0.061	−0.20104***	0.061
West					−0.15628**	0.066	−0.16527**	0.066
North-east (base = central)					−0.22861***	0.065	−0.23677***	0.065

Table 3 Empowerment: probit–ordered probit system: joint FIML estimates

	Women's empowerment equation							
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	0.16752***	0.012	0.95436***	0.032	0.95398***	0.032	0.69377***	0.044
Education difference	−0.01633***	0.002	−0.00645***	0.002	−0.00638***	0.002	−0.00794***	0.002
Female lbr. mkt. participation	0.00054***	0.3548D−04	0.00064***	0.3911D−04	0.00064***	0.3918D−04	0.00064***	0.3919D−04
Female birth family status	0.31940***	0.021	0.29698***	0.021	0.29750***	0.021	0.29618***	0.021
Female home ownership	0.64154***	0.024	0.58711***	0.025	0.58707***	0.026	0.59437***	0.026
Women's welfare program			−0.0131	0.015	−0.0134	0.015	0.02091	0.016
Age of head			−0.01685***	0.001	−0.01684***	0.001	−0.01691***	0.001
Female exposure to media			0.16013***	0.015	0.16017***	0.015	0.17003***	0.015
Female head			0.66510***	0.021	0.66584***	0.021	0.66404***	0.021
High caste			−0.0122	0.020	−0.0122	0.020	−0.0198	0.020
Distance to district HQ			−0.00255***	0.000	−0.00255***	0.000	−0.00222***	0.000
Wage employment program			−0.06965***	0.015	−0.06957***	0.015	−0.05783***	0.015
North							0.27805***	0.035
South							0.30207***	0.041
East							0.17517***	0.036
West							0.21862***	0.038
North-east (base = central)							0.19127***	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	−0.09001**	0.043	−0.09258**	0.044	−0.0582	0.046	−0.0557	0.045

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. These variables represent standard intra-household distribution factors that are used in the empirical bargaining power literature. 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 estimate specifications in which the $\mathbf{Z}_i$ matrix contains variables that directly affect both adoption and woman's influence. 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 women's influence, which we use to test our main hypothesis. For a variable that appears in *both* the adoption and the influence equation, the model estimates both the direct effect of the variable on adoption, as well as its indirect effect via its impact on women's influence, which, in turn, affects adoption. Additionally, conditioning on the error correlation allows us to disentangle causal from common unobserved heterogeneity effects of influence and adoption.

4.1.3 Results for the joint adoption-women's influence model

Tables 2 and 3 report the findings of our FIML estimates of the joint model for adoption and influence. The adoption parameters appear in Table 2 and the influence parameters in Table 3. We present the results for four different specifications: in model 1, the $\mathbf{Z}$ matrix in the influence equation (18) includes only distribution factors, which are assumed to affect adoption [Eq. (17)] only indirectly through λ_i; model 2 extends the set of explanatory variables in (18) to include variables that affect adoption directly as well as indirectly; model 3 includes regional control variables in (17); Model 4 includes them in (18) as well.

The coefficient on women's influence in (17) is positive and highly significant across our four different specifications (Table 2, row 2). This finding provides strong evidence that the probability of MCS adoption increases significantly when women belong to the highest influence category, relative to when they belong to the lowest one, and is consistent with our theoretical prediction about the positive impact of women's influence on adoption. The positive and significant influence coefficient is simultaneously evidence of women's higher marginal preferences for smoke reduction than men's (c.f. the discussion immediately above Proposition 1 on p. 13).

We obtain another interesting result relating to the coefficient on the female head variable. Female headship has a negative direct effect on adoption, but a positive indirect effect, by increasing women's influence. This finding reveals a complementarity between seemingly opposing views in the literature about the effect of female headship on modern technology adoption. On the one hand, we would expect female-headed households to adopt with greater frequency than male-headed ones, because, by definition, women in the former have a greater intra-household role, together with a higher marginal preference for smoke reduction. On the other hand, we would expect female-headed households to adopt *less* frequently because they are relatively poorer and, hence, less able to afford the start-up cost of a new stove connection. Moreover, according to Kohlin et al. (2011), conditional on household wealth, women may be disadvantaged relative to men in dealing with the transaction costs associated with adoption. Our findings are consistent with both views. We find a direct negative effect of female headship on adoption (Table 2, row 6) and an indirect positive effect on adoption due to the fact that women in female-headed households have, by definition, a higher intra-household role (Table 3, row 9).

Consistent with the previous empirical literature on MCS adoption, we find highly significant positive effects of household wealth and education on adoption. 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 male household head's age on adoption, which operates indirectly, through its negative effect on women's intra-household influence (Table 3, row 7).

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,[6] or that the costs of transitioning to a new cooking technology increases with the scale of the household's cooking activity. Moreover, larger households may be more traditional and, hence, less inclined to adopt modern technologies. Household size is an indicator of the extent to which a household is "traditional," since earlier generations of rural Indians were more likely to live together as "joint families" than new generations which are experiencing a break-up of the family into a number of smaller independent units. Consistent with our expectations, access to credit—proxied by the presence of a bank in the village in which a household is located—as well access to electricity both have positive and significant effects on adoption. We do not find statistically significant *direct* effects 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 *indirect* effects on adoption, mediated through women's intra-household influence. Women's exposure to information from public media has a strong and positive effect on their influence—an effect that is robust across all four specifications (Table 3). This suggests that the empowering effect of mass media, supported by a growing literature on the impacts of television on gender roles, has a positive effect on household technology adoption (e.g., Jensen and Oster 2009).

Remoteness has a negative effect on adoption through its indirect negative effect on women's influence. The availability of additional wage earning opportunities in villages also lowers women's influence, 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 attract men to self select

[6] For example, Harrell and Young (2013) found that one of the major impediments to MCS adoption in Uganda was that potential purchasers considered the modern products too small for cooking with large families.

into the program. If this is the case, then our results reflect the consequent decrease in female influence due to their lower relative contributions to total household income.

We find the effects on women's influence of all distribution factors to be consistent with theoretical predictions. The male–female education gap has a large negative effect on influence, while female labor market participation, birth status and home ownership all have strong positive effects. These findings are robust across all specifications and are consistent with a large literature showing that intra-household roles matter for household decision-making. In particular Allendorf (2007) finds that as women's participation in the labor market increases, so too does their decision making authority within the household. Studies have also shown that women's ownership of property is associated with increased decision-making authority (Swaminathan et al. 2012). Surprisingly, we find no evidence that women's intra-household influence is enhanced by the presence of a women's welfare program in a village.

The statistically significant correlation between the error terms in models 1 and 2 suggest the presence of unobserved household heterogeneity that affects both women's influence and adoption. Accounting for significant correlation increases our confidence that women's influence has a positive effect on adoption, since the correlation holds constant common unobserved factors that affect both variables. We find significant regional variation in the mean levels of both influence and adoption, but after including regional controls the correlation between equations is no longer significant.

4.2 A stochastic threshold model of influence

4.2.1 Alternative sources of women's influence

In the model analyzed in Sect. 4, we maintain the assumption that the probability of observing a particular outcome is determined by the same process across all households. In particular, we assume that the probability of observing a woman with a given level of intra-household influence, conditional on her skills or ideosyncratic attributes relative to male members of her household, is constant across the sample. This assumption, while standard, imposes a restriction on the process through which power is determined in our conceptual framework: in Eq. (15), whose general form is $\lambda_i = \Lambda(\chi_i; \chi_k)$, the assumption implies that (15) has the special form $\lambda_i = \Lambda(\chi_i, \chi_0)$, where χ_0 is a constant; in particular, it is independent of the societally constructed gender norms which are indexed by k in our theoretical model (see p. 11). If, however, this constant χ_0 does in reality differ systematically with culture, ethnicity or other sources, our regression results and, of specific interest to us, the influence coefficient in the adoption equation (17), will be contaminated by not taking into account the unobserved heterogeneity. Moreover, it could be the case that the positive effects of intra-household influence on adoption that we have reported are driven by unmodeled shifts in χ_0, rather than by the variations in women's ideosyncratic attributes that are captured by the $\mathbf{Z}_i$ matrix. One possible example of such a shift relates to caste differences: typically, higher caste Indian women are subject to greater restrictions than lower caste women relating to the types of employment they can engage in outside the household. Because of this, a woman's capacity to contribute to her household's income is, other factors held constant, more constrained, the higher is her caste, and since relative income contribution is an important driver of intra-household influence, this caste-related factor may reduce her bargaining power.

There is another problem with the assumption of constant thresholds in Eq. (19): it implies that the mapping from the observed to the latent is undistorted in the cross-section. Specifically, the mapping from women's ranking of their household influence to their "true" influence will be undistorted only if there exists a universally accepted, "objective" scale along which to measure womens' influence. In the absence of such a scale, individuals from different cultures, ethnicity and socio-economic status might assign different meanings to each of the four points on the scale on which they were asked to rank themselves. For example, we might expect that women with high levels of education would, *objectively*, have more autonomy in their households than women with less education. However, since educational experiences may sensitize women to the topic of gender equity, highly educated women's *subjective experience* of the relatively few actual constraints on their autonomy may cause them considerable distress, while, on the other hand, less educated women, who have been exposed less to gender equity issues, might be more reconciled to much more extensive restrictions. 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 no objective measure is available.[7] 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 have different subjective interpretations of the different points on the scale (see e.g., Sen 2002).

This problem has two consequences for our preliminary finding that women's influence has an effect on a household's MCS adoption decision. First, if the mapping between observed and unobserved influence differs systematically across households with different cultures and ethnicity, then, even though the influence variable has a significant and positive impact on adoption, we cannot infer that women can impact the adoption decision by becoming more effective bargainers. Consequently, our adoption analysis might lead us to conclude there is a strong rationale for government polices that seek to increase adoption by empowering women; but this conclusion could be based on a misreading of the data, specifically, a failure to take into account the threshold effects. Second, if the mapping between observed and unobserved influence differs systematically across households due to

[7] To motivate the role that an objective scale might play, suppose we were studying child growth rate, and the survey question was: "how many inches did your baby grow in the last month?" In this case, the subjective component arising from different interpretations of the question would be relatively low, since inches are inches, notwithstanding measurement errors. On the other hand, if the survey question were "do you like Indian food to be served mild, median, spicy, or hot?" both subjective and objective components would play a role. Indeed one could conceivably administer this question in Delhi and Des Moines, and find that respondents 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.

pure reporting errors—for example, based on the characteristics of individual respondents—then the coefficient on women's influence in the previous section will be inconsistent. For these reasons, it is important to examine whether the intra-household distribution factors retain their expected signs and statistical significance, after we control for unobserved heterogeneity that may create a distortion in the mapping between the observed and unobserved influence scales. If they do, then we can more confidently infer from the positive influence coefficient in Eq. (17) both that women's influence matters in adoption decisions *and* that women can impact the adoption decision through bargaining.

We incorporate heterogeneity in χ_0 by specifying that the thresholds of our ordered probit model of women's influence (18) depend on covariates (Ierza 1985). Specifically, we replace χ_0 by χ_k, where k indexes four sources of heterogeneity. First, since it is difficult to define a full set of threshold covariates on social and cultural norms based on observed variables alone, we allow the thresholds to be stochastic (Weterings et al. 2012). To this end, we specify the thresholds to be functions of village level random effects which exploit heterogeneity in social norms across over the 1440 villages in our sample which, arguably, are culturally homogeneous within. Here, we are maintaining the hypothesis that there is significant heterogeneity in cultural and social norms across over the 1440 villages in our sample, but cultural and social homogeneity within each village. Our rationale for this approach is that in India, villages are relatively homogeneous units, in which people with common social values agglomerate or have lived for generations: for this reason, social and cultural norms are likely to vary more across villages than within them. Second, we include two observed measures of social norms and cultural differences across households, caste and female headship. Third, we allow each of the four distribution factors included on the right hand side of (18) to have an effect through the threshold equation (19), in addition to its effect on women's influence. This would account for shifts in the χ_k's due to subjective interpretations of power in households with more "skilled" women. For instance, since relative education is one of our determinants of women's influence we would expect women who are less educated than the men in their households to be less likely, on objective grounds, to belong to the high influence category. However, since they may have a relatively less demanding, subjective sense of what it means to belong to this category, they may over-report their level of empowerment. Finally, we include as threshold shifters a set of survey respondent characteristics which account for shifts in the χ_k's due to subjective interpretations of the power scale by the respondent. For example, older or more educated female respondents may have a higher threshold for what constitutes high power and, thus, underreport on that category relative to younger respondents. Specifically, we include three respondents characteristics—the age and education of the respondent, the number of children she has and whether a non-household member was present during the interview.

Following Greene and Hensher (2010), our stochastic threshold model for women's influence specifies the thresholds in Eq. (18) as:

$$\mu_{kj} = \mu_{kj-1} + \exp\left(c_{0j} + \mathbf{c}_1'\mathbf{y}_k + c_{2j}\Omega_k\right), \quad j = 1, 2. \tag{20}$$

where c_{0j} denote the constant terms in each threshold μ_j, $j = 1, 2$; $\mathbf{c}_1'$ denotes the effect of a vector of observed determinants, $\mathbf{y}_k$, on the thresholds, and c_{2j} denotes the standard deviation coefficients on the unobserved village random effects Ω_k, which are assumed to be *i.i.d.* normal. As before, we use the normalizations $\mu_{-1} = -\infty$, $\mu_0 = 0$, $\mu_3 = \infty$. Note that our constant threshold specification (model 1) in the previous section is nested within the model above and is obtained when c_1 and c_2 are both zero. The model is estimated after integrating out the random effects using simulated maximum likelihood.

4.2.2 Results for the model in which influence is decomposed

Table 4 presents the results of the influence equation, estimated using our stochastic threshold ordered probit specification. Accounting for cross-sectional differences in the mapping from unobserved to observed influence 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

Table 4 Empowerment: stochastic threshold model—simulated MLE estimates

	Coefficient	SE
Women's empowerment equation		
Constant	0.14174***	0.006
Education difference	−0.00569***	0.001
Female labor mkt. participation	0.00071***	.0004
Female birth family status	0.36186***	0.018
Female home ownership	0.83864***	0.020
Intercepts of random thresholds μ_1 and $\mu_2 (a_{0j})$		
a_{01}	0.60806***	0.035
a_{02}	−0.48413***	0.048
Standard deviations of random thresholds (a_{2j})		
a_{31}	0.40996***	0.013
a_{32}	0.61320***	0.051
Threshold covariates $(\boldsymbol{a}_1')$		
Education difference	−0.00401**	0.001
Female labor mkt. participation	0.00033***	0.0001
Female birth family status	0.04266**	0.110
Female home ownership	0.34767***	0.019
Female head	−0.97328***	0.069
High caste	0.03708*	0.019
Non-household member presence	0.0143	0.031
Respondent age	0.00417***	0.0008
Respondent education	−0.0018	0.002
Respondent no. of children	−0.04043***	0.005

show up on a common objective scale of women's influence, and which would accurately reflect the extent to which women can impact 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 respondents' interpretation of the concept of women's influence. Controlling for subjective effects, we find that the male-female education gap negatively and significantly effects the probability that women belong to the highest influence category. Similarly, women's labor market participation, their higher birth family status relative to their husband's and their property ownership all significantly and positively effect women's influence. Interestingly, relative to the fixed threshold model (model 1) in the previous section, the magnitude of the education gap coefficient is smaller, while the magnitudes of the rest of the distribution factors are larger in Table 4.

In addition to the objective effect of the education gap on women's influence, we find that in households where women are relatively less educated, the power thresholds are scaled back. That is, the estimated μ_{ij}'s in (20) are lower, the higher is the education level of woman i, relative to the men in her household. This is evident from the negative and statistically significant coefficient on the male–female education gap variable in the threshold specification, which suggests that households in which women are less educated than their male housemates are more likely to report that women have the highest category of influence. Consistent with intuition, the subjective effects of three other women's characteristics—greater participation in the labor market, relatively affluent birth families, and property ownership—work in the opposite direction: the thresholds for these households are scaled up relative to the population, implying that women with these characteristics have more stringent notions of what it means for them to have significant influence. Such women are thus less likely, other things being equal, to report that they belong to the highest influence category.

The large number of significant threshold explanatory variables in Table 4 indicates that the model accounts for considerable heterogeneity across households. The statistically significant standard deviations on the village random effects, along with the means, suggest that groups of households with different social norms and cultural attributes interpret our power scale in significantly different ways. Female-headed households have lower thresholds (a negative threshold coefficient) for what constitutes high power and are, therefore, less likely to report themselves as belonging to the highest influence category. Interestingly, we find that households from higher caste 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. We find that older respondents have higher thresholds or a more stringent definition of power. Thresholds for respondents with a larger number of children are scaled down. The respondent's education, and whether or not an outsider (not a member of the household) was present during the interview, had no effect on the thresholds.

The results summarized above strongly reinforce our earlier findings and are evidence that, if distribution factors could be measured on an objective scale, they would impact women's influence in the directions predicted by theory. Since the distribution factors operate at the household level, and through clearly defined channels such as education, it should be possible to design polices that could target these channels, or other distribution factors that increase women's bargaining position. Such policies could, then, potentially increase women's bargaining power and improve household outcomes when women's preferences differ from men's. In the context of this study, they could increase the rate of MCS adoption.

5 Conclusions

We examine the barriers to adoption of MCS's in rural India, using a large, nationally representative dataset. We develop a collective household model to derive testable hypotheses about whether women's intra-household influence, together with their relatively strong marginal preference for MCS's, affect household adoption of this technology. Using a joint adoption-influence econometric model, we find compelling evidence that women's intra-household influence significantly increases households' MCS adoption. We conduct additional analysis to distinguish between alternative sources of women's influence, which has implications for MCS dissemination policies. While we find that significant variation in women's influence across rural India can be attributed to cultural and other sociological factors, the coefficients on all of our ideosyncratic, household-level distribution factors retain their expected signs and significance levels, confirming that the effect of intra-household influence on adoption has a significant "bargaining power" component. We conclude that the extent of women's role in household decision making cannot entirely be explained by societally constructed gender norms, and that factors ideosyncratic to the household, such as women's individual bargaining and negotiation skills, have an explanatory role.

Our results suggest that MCS programs may be able to increase adoption if stoves are marketed in ways that empower women. For instance, subsidies for MCS purchases that specifically target women could potentially strengthen their intra-household bargaining positions, and thereby harness their relatively strong marginal preferences for MCS's. 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 MCS adoption rates.

Another implication of our results is that there may be an additional channel for increasing adoption—through the empowerment of women which would mobilize their higher preferences for MCSs. One policy implication is to use public media (radio and television) which have been shown to be an important means of empowering women with knowledge about the health effects of traditional cookstoves. Women have to be targeted specifically to receive this information, perhaps by bundling the stove related information with programs known to be popular among women. Our results also, lend support for the effectiveness of policies that link women's empowerment and technology adoption, more generally. For example, a recent initiative of "Feed the Future" seeks to empower women by promoting women's land ownership, leadership, education and skills, and control over credit in order to scale up stove dissemination programs and to encourage female farmers adoption of new agricultural technologies (Hart and Smith 2013; FAO 2011). Apart from this proactive approach of empowering women, our results support the view that policies should also focus on offsetting men's relatively lower likelihoods of purchasing MCSs. For example, our results are consistent with Miller and Mobarak (2011)'s suggestions for packaging cookstove technologies with goods that that men appreciate but cannot purchase separately from a cookstove. An example is a Biolite improved cookstove, which generates a small charge for cell phones while the stove is used for cooking, making it attractive to men.

Appendix

The likelihood function for our model is can be derived by rewriting the adoption equation (17) as $Prob(v_i = 1) = \Phi(\boldsymbol{\alpha}'\mathbf{X_i})$ and the influence equation (19) as $Prob(\lambda_i = j) = \Phi(\mu_j - \mathbf{b}'\mathbf{Z}_i) - \Phi(\mu_{j-1} - \mathbf{b}'\mathbf{Z}_i)$. The explanatory variable matrices X and Z contain common elements but are not identical to allow identification. The likelihood function is built up from the joint density of the random variables v_i and λ_i :

$$
\begin{aligned}
L = & \prod_{v_i=0,\lambda_i=0} \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, -\boldsymbol{\beta}'\mathbf{Z}_i; -\rho) \\
& \times \prod_{v_i=0,\lambda_i=1} \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, \mu_1 - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho) - \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, -\boldsymbol{\beta}'\mathbf{Z}_i; -\rho) \\
& \times \prod_{v_i=0,\lambda_i=2} \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, \mu_2 - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho) - \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, \mu_1 - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho) \\
& \times \prod_{v_i=0,\lambda_i=3} \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, \infty - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho) - \Omega(-\boldsymbol{\alpha}'\mathbf{X}_i, \mu_2 - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho) \\
& \prod_{v_i=1,\lambda_i=0} \Omega(\boldsymbol{\alpha}'\mathbf{X}_i, -\boldsymbol{\beta}'\mathbf{Z}_i; \rho) \\
& \times \prod_{v_i=1,\lambda_i=1} \Omega(\boldsymbol{\alpha}'\mathbf{X}_i, \mu_1 - \boldsymbol{\beta}'\mathbf{Z}_i; \rho) - \Omega(\boldsymbol{\alpha}'\mathbf{X}_i, -\boldsymbol{\beta}'\mathbf{Z}_i; \rho) \\
& \times \prod_{v_i=1,\lambda_i=3} \Omega(\boldsymbol{\alpha}'\mathbf{X}_i, \infty - \boldsymbol{\beta}'\mathbf{Z}_i; \rho) - \Omega(\boldsymbol{\alpha}'\mathbf{X}_i, \mu_2 - \boldsymbol{\beta}'\mathbf{Z}_i; -\rho)
\end{aligned}
$$

where Ω is the bivariate normal distribution.

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