Prices, Peers, and Perceptions: Field experiments on improved cookstove adoption in Ghana

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ABSTRACT

Despite their potential health and social benefits, adoption of improved cookstoves has been low throughout much of the world. Explanations for low adoption rates of these technologies include *prices* that are not affordable for the target populations, limited opportunities for households to learn about cookstoves through *peers*, and *perceptions* that these technologies are not appropriate for local cooking needs. The P3 project, which is being conducted in the Kassena-Nankana Districts of Northern Ghana, employs a novel experimental design to explore each of these factors and their interactive effects on cookstove demand, adoption, and exposure outcomes. Leveraging an earlier improved cookstove study, the central design of the P3 experiment involves offering two types of improved biomass stoves at randomly varying prices to peers and non-peers of households that had previously received similar stoves for free. Preliminary analyses of households' stove orders are presented in this paper. Overall, willingness to pay for stoves is higher than expected based on results of stove auctions, and aligns fairly well with stated preference estimates from an earlier study in the area. We find some initial evidence that learning about improved stoves from prior recipients influenced the peer group's choices. Peer households appeared to value each of the stoves less individually, but had higher demand for the stove combination (one of each type of stove) compared with the non-peer group. Ongoing measurements and analysis will assess impacts of prices and peers on whether households actually follow up on their initial orders (i.e., make payments), as well as on perceptions of stove quality, use of traditional and improved stoves, and household air quality outcomes.

KEYWORDS: Cookstoves; technology adoption; peer effects; household air pollution; behavior change; global health

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I. Background

Low adoption rates of potentially health-enhancing technologies have been observed in a number of cases across a variety of contexts; examples include bed nets (Cohen and Dupas 2010), latrines (Pattanayak et al. 2006), deworming drugs (Kremer and Miguel 2007), and condoms (Ali et al. 2004), among many others. Explanations for this phenomenon tend to focus on three key factors: the *prices* of these technologies and the role of subsidies (Pattanayak et al. 2009, Cohen and Dupas 2010, Ashraf et al. 2013), the effect of *peers* and social learning (Kremer and Miguel 2007, Dickinson and Pattanayak 2008, Conley and Udry 2010), and the ways in which users' *perceptions* of technologies affect subsequent adoption decisions (Kremer and Miguel 2007, Ashraf et al. 2013, Miller and Mobarak 2013). The aim of this project is to investigate the interactions among these three factors in determining adoption of improved cookstoves, a technology with potential health, social, and environmental benefits.

Cooking with biomass over open fires is a widespread practice throughout much of the developing world. Wood, dung, agricultural residues, and charcoal produce large amounts of respirable particles, carbon monoxide, and other toxic pollutants when used to fuel simple cooking stoves (Smith 1987). A growing body of evidence links household air pollution (HAP) to acute lower respiratory infections in young children and chronic obstructive pulmonary disease and lung cancer (for coal) in adults (Ezzati and Kammen 2001, Smith et al. 2004, Lim et al. 2012). Biomass cooking also impacts regional and global climate through black carbon particulates and other emissions (Bond et al. 2004). Furthermore, gathering fuels is a time-consuming activity in locations where environmental damage has often already made resources scarce. This time burden, which falls disproportionately on women, could be better spent on domestic care or income-generating activities, aggravating the problem of "time poverty" (Blackden and Wodon 2006).

While a multitude of technologies exist that could potentially address the suite of problems linked to current biomass cooking practices, efforts to disseminate these technologies and promote changes in cooking behaviors have often fallen short (Hanna et al. 2012, Smith et al. 2014). The Global Alliance for Clean Cookstoves, a public-private partnership currently in its second phase of "investment and innovation," has set a goal to foster the adoption of clean cookstoves and fuels in 100 million households by 2020 (Anthony 2010). However, consistent adoption of cleaner stoves has proven elusive in practice at larger, community-level scales. The well-known RESPIRE study provided an improved chimney woodstove to households in highland Guatemala and saw encouraging results, finding a significant reduction in carbon monoxide exposure for groups receiving the clean stove over an 18 month period (Smith-Sivertsen et al. 2009). On the other hand, randomized trials of a locally-made mud stove in India achieved disappointing initial adoption and maintenance rates and, in the long run, failed to reduce exposure to dangerous air pollutants (Hanna et al. 2012). These authors specifically contrasted their intervention with the RESPIRE study and argued that they provided households with greater ability to reveal their valuation in usage rates: stoves were locally made and significantly cheaper, were not inspected weekly (Smith et al. 2009), and were followed for a longer period of time. In response, Kirk Smith (who led the RESPIRE study) argued that the Indian "improved" stove was not truly an improvement over existing technologies since it failed to alter combustion and reduce smoke in any meaningful way (Smith 2012). Essentially, both sides of this debate contended that *low perceived benefits* of the cookstove technology led to low adoption and use. The cookstove example thus presents itself as a useful context for examining the challenges and dynamics of technology adoption.

Prior Research on Technology Adoption

Technology adoption continues be a central research topic in the social sciences because of its importance in understanding environmental, development, and health outcomes and because of the kaleidoscope of models explaining different economic, psychological, and sociological factors at play. Two key strands of literature we summarize here examine the roles of prices and peer effects on technology adoption.

Prices and technology adoption and use

Setting subsidy and end-user price levels for a new technology reflects a fundamental tension between rapid diffusion and sustainability (Mobarak et al. 2012, Dupas 2014). On the one hand, subsidizing adoption of socially beneficial technologies may be necessary to promote widespread adoption, at least in the short-run. Indeed, recent evidence has shown that new technologies offered at a positive price tend to exhibit much lower demand than identical products offered for free. The most recent World Development Report (World Bank 2015, see Figure 1) details numerous examples of this phenomenon. In one example that is particularly relevant for this study, Mobarak and coauthors (2012) analyzed a field experiment with the distribution of cookstoves in Bangladesh. The researchers found demand for these modern stoves to be extremely price elastic, with only 5% of households purchasing the stoves with no discount and a 50% discount yielding 8-12% higher demand (relative to the full cost treatment).

On the other hand, many argue that goods given away for free or at low cost will be *used* at lower rates than goods for which users pay higher prices. There are at least two theoretical foundations for this hypothesis. First, price-based incentives for new technologies (or any scarce good) ensure allocation of goods to those valuing them the most (a basic principle in economics). Second, higher prices may lead potential users to perceive that a product is of higher quality (Bagwell and Riordan 1991), thus encouraging higher use. Empirically, however, there is little evidence to support this hypothesized positive relationship between price and technology use. In one of few studies to directly test this hypothesis, Cohen and Dupas (2010) analyzed data from a randomized controlled trial of bednet distribution in Kenya in which health clinics distributed bednets freely or partially subsidized at four different end-user price levels (between \$0.15 and \$0.60 per net). The researchers identified significantly price-elastic demand for bednets: Clinic patients charged the highest price in the experiment exhibited 60% lower demand for bednets relative to the free distribution group. Moreover, despite thorough statistical analysis, Cohen and Dupas did not find evidence that the free distribution group exhibited lower usage rates (conditional on ownership) than the partially subsidized groups. Furthermore, the free distribution group was the only treatment group for which the researchers found a statistically significant health impact (reduced anemia). To our knowledge, these authors did not directly examine the relationship between price and perceived quality of bednets as an intermediate factor affecting product use.

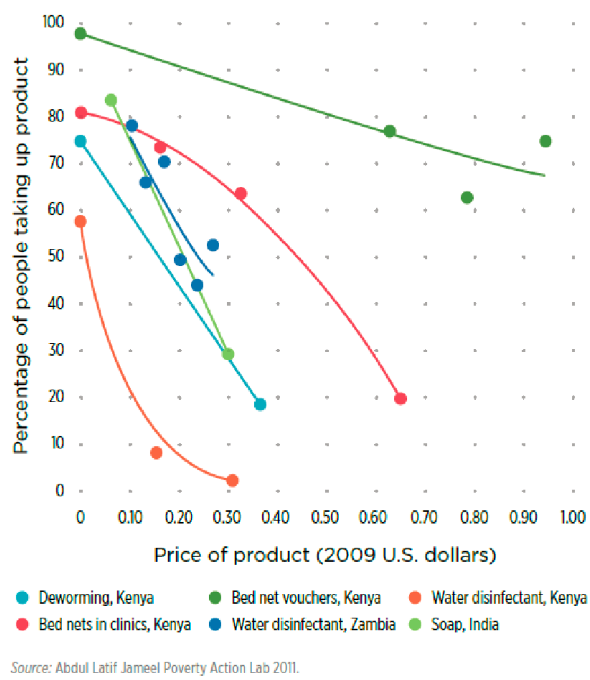

Figure 1: Relationship between price and technology adoption for various health products.

Thus, empirical evidence to date seems to indicate that highly subsidized or free distribution of health-promoting technologies: a) may be required to promote their initial adoption, and b) does not appear to reduce subsequent technology use (although the latter finding has a thinner evidence base and should be tested more broadly). Yet free distribution strains public resources and may not be sustainable over time or scalable to population-level technology diffusion. Additional work is thus required to examine the dynamics of diffusion over time and space. One particular question involves the possibility that subsidizing adoption to an initial group of users can lead that group's peers to learn about and subsequently adopt a technology and, assuming the technology is useful, positively affect individuals' willingness to pay (WTP) for the technology.

Peer effects and technology adoption

In contrast to prices, peer effects present the possibility of a positively reinforcing feedback for sustaining adoption and takeoff of new technologies. The power of social contagion in technology adoption has been measured in a number of contexts (e.g., Bollinger and Gillingham 2012). Miller and Mobarak (2013) estimate peer effects on efficient cookstove adoption in Bangladesh, by conducting randomized, sequential cookstove rollout first with opinion leaders, then with a first round of randomly selected members of the general population (in the same neighborhoods as the opinion leaders), and then with social contacts of the first round households. Their results suggest statistically significant and positive peer effects from opinion leaders' adoption behaviors (at least in some cases), but social ties to first round participants are found to *reduce* the likelihood of adoption among second round households. The authors' interpretation of this finding is that second round participants held initially high expectations about the modern stoves, and revised these expectations downward via information from social contacts. This negative peer effect finding and its interpretation are similar to Kremer and Miguel's (2007) analysis of deworming drugs in Kenya. Yet to our knowledge, neither study explicitly measured expectations or beliefs about product quality. Both of these cases highlight the fact that while the increasing availability of experimental data and appropriate econometric methods for analyzing these data have gone a long way toward solving Manski's (1993) "reflection problem" and enabling identification of peer effects, this research has also raised a number of new questions about the causal mechanisms underlying observed effects.

In light of the previous research outlined above, we aim to contribute to a more scientific understanding of the interactions between economic incentives ("prices"), social learning ("peers"), and subjective beliefs ("perceptions") in technology adoption dynamics. Specifically, we posit that prices and peer effects both operate – at least in part – through separate and interactive effects on perceptions of a technology's quality and benefits.

Conceptual Model

Figure 2 presents our conceptual model of how we expect prices, peers, and perceptions to interact, based on previous research. Prices can be expected to have both direct and indirect influences on key outcomes (technology adoption and use): The direct effect (the economic "law of demand") is expected to be negative, while it is possible that there is a positive indirect effect on both adoption and use via higher perceptions of technology benefits for higher-priced products. Peer effects can be expected to affect individual adoption and use through effects on individuals' perceived value of the new technology. This effect can be negative or positive.

Importantly, the conceptual model in Figure 2 also highlights the potential feedbacks (the dashed arrows) that can confound causal identification, and which our experimental design seeks to address. First, a number of factors determine prices for a new technology in an observational setting, including supply and retail costs. We will address this confounding feedback using prices which are randomly assigned across groups of households. Second, peer effects are well-recognized for their potential to generate positive feedback loops. We will control for this confounder by sampling households neighboring participants in a previous cookstove intervention, in conjunction with the recruitment of new groups of households unexposed to the technology. This identification strategy for peer effects appears unique compared to previous research (Kremer and Miguel 2007, Bobonis and Finan 2009, Miller and Mobarak 2013).

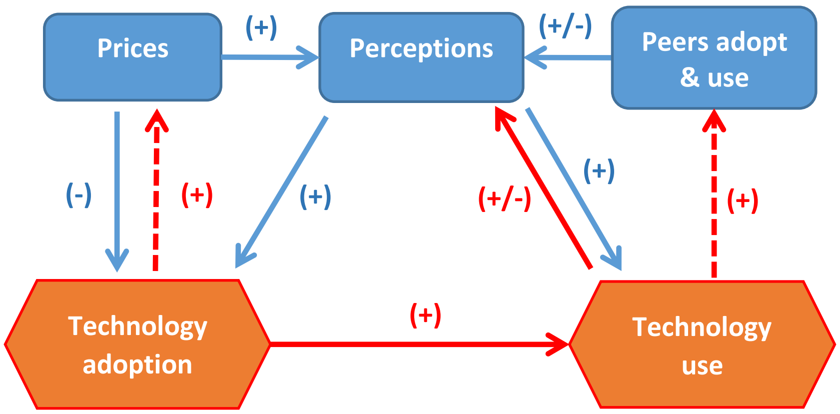

Figure 2: Influence diagram of the factors of technology adoption dynamics. The solid arrows in the diagram are influences that this study will examine in detail. The dashed arrows are potential confounding feedbacks that our identification strategy will address. The signs in parentheses indicate whether effects are expected to be positive or negative, based on previous literature.

Finally, an important question for sustainability science is how subjective expectations change following technology adoption and subsequent use, and how these revised expectations determine long-term use. For example, we might hypothesize (e.g. based on the Prospect Theory literature (Kahneman and Tversky 1979)) that discovering a new technology to yield smaller than expected benefits may be have a greater downside effect on usage than the upside effect of finding the technology to have greater than expected benefits.

Additional key questions emerging from this model are how the individual factors affecting key outcomes of interest are mediated by the other factors. A standout issue along these lines is the possibility that peer effects may dampen the role of prices in subjective perceptions of technology quality. This is one hypothesis suggested by Ashraf et al. (2013), who conducted an information-based interventions in the case of improved water filter subsidization in Zambia and found that information provision increased the price elasticity of demand, making price subsidies more effective. The authors remain agnostic on the causal mechanisms behind this finding, but suggest that uninformed consumers may use price as an indicator of product quality.

A theoretical economic model of peer-price interactions in technology adoption

In the experimental design described below, there are two sources of econometric identification that will be used to identify the effects of peers and prices on perceptions and technology adoption behaviors. We here develop a brief theoretical model that characterizes how the exogenous factors in our experiment could be hypothesized to affect the primary variables of interest. The basic assumptions of the model are that, *ex ante*, individuals are uncertain about the potential benefits of a new technology, and that they use multiple potential information sources – including peers and implicit information embedded in prices – to form their subjective expectations about the technology's benefits.

Suppose an individual experiences random indirect utility of $V(Q, p) + \epsilon$ from adopting a technology defined by a vector of characteristics Q (e.g. product quality, longevity, maintenance costs, etc.) and costing a price of p to obtain. The ϵ term is an additive random utility component (McFadden 1974). For exposition assume that Q is a single variable summarizing product quality, and that marginal utility is decreasing in price and increasing in quality ($\partial V/\partial p < 0$ and $\partial V/\partial Q > 0$). Also suppose the technology has only two possible quality levels high (H) and low (L), with indirect utility $V_H(p) + \epsilon$ under high quality and $V_L(p) + \epsilon$ under low quality.

Ex ante, the decisionmaker knows the price p but is uncertain about quality. Suppose the decisionmaker has a prior belief quality, which – in the absence of better information – may be a function of the product's price p (as suggested by Judd and Riordan 1994 and others). Summarize this belief via the prior probability of high quality $\pi(p)$. This hypothesis can then be stated as $\partial\pi/\partial p > 0$: higher prices suggest higher quality to otherwise uninformed individuals.

The individual will then adopt the technology if and only if the expected utility from adoption is positive, i.e. $\bar{V} + \epsilon \equiv V_H\pi + V_L(1-\pi) + \epsilon > 0$. Integrating the random utility ϵ component out of V, the probability of adoption is therefore: $P_\pi(p) \equiv \Pr[V_H\pi + V_L(1-\pi) + \epsilon > 0 | \pi(\cdot), p]$.

An increase in the price p on the adoption probability P_π is the net effect of a direct negative effect of higher prices on utility and the indirect positive effect of higher prices on beliefs in higher quality:

$$\frac{\partial P_\pi}{\partial p} = \frac{\partial P_\pi}{\partial \bar{V}} \cdot \left[\underbrace{\frac{\partial V_H}{\partial p}\pi + \frac{\partial V_H}{\partial p}(1-\pi)}_{\substack{\text{Direct} \\ \text{price effect } (-)}} + \underbrace{\frac{\partial \pi}{\partial p}(V_H - V_L)}_{\substack{\text{Indirect} \\ \text{quality effect } (+)}} \right]$$

From this we can see that the effect of prices on demand for the new technology should in theory be attenuated by the use of price in the formulation of prior beliefs about quality.

Now consider an individual who updates her beliefs based on prior adoption and use of the technology among her social contacts. Specifically, the individual observes surrounding levels of product usage e among prior adopters, as well as the characteristics of surrounding households. A Bayesian would then update her beliefs based on this information to obtain a posterior probability of high quality ρ_H:

$$\rho(e,p) = \frac{\gamma_H(e)\pi(p)}{\gamma_H(e)\pi(p) + \gamma_L(e)[1-\pi(p)]}$$

where $\gamma_H(e)$ and $\gamma_L(e)$ are the likelihoods of observing usage levels e conditional on the technology being, respectively, high or low quality.

The adoption probability P_ρ with social learning via posterior beliefs ρ is therefore:

$$P_\rho(e,p) \equiv \Pr[V_H\rho + V_L(1-\rho) > 0 | \rho(\cdot), e, p]$$

We can use this model to infer in theory how prior adopters' usage behavior and the current price should affect the adoption probability for an informed and uninformed individual. To see this, we must first examine how the posterior belief changes with regard to these factors. For this purpose, a common assumption in this literature is that the likelihood ratio γ_H/γ_L is strictly increasing in e, which implies first- and second-order stochastic dominance of γ_H over γ_L. This is often referred to as the monotone likelihood ratio property, and captures the notion that the higher the observed usage e among prior adopters, the more likely it is that the technology is of high quality (Milgrom 1981). Under this condition, it can be shown that $\partial\rho/\partial e > 0$ and that $\partial P_\rho/\partial e > 0$: Expectations about quality and subsequent adoption increase with peers' usage.

The interaction effect of social learning through e and price p on demand P_ρ is more subtle. Intuitively, the more informative a realization of e is, the less weight the prior plays in the adoption decision, and hence the lower the information effect of prices. Using the above model, it can be shown that if the prior belief already puts more weight on the quality level with a relatively greater likelihood of yielding observed behavior e, then price p has a greater effect on prior beliefs rather than posterior beliefs, i.e. $\partial\pi/\partial p > \partial\rho/\partial p$. This is because the posterior beliefs incorporate learning based on peers' behavior (through e), and thus relies less on "information" conveyed by p. In terms of the price-elasticity of adoption the following pattern emerges from the model: Relative to the uninformed case (P_π), an increase in usage of prior adopters e leads to a higher price-elasticity of demand when the observed e adds confidence (reduces uncertainty) in existing prior beliefs. For empirical purposes, one implication is that it is necessary to consider nonlinear effects of social learning on the price elasticity of demand. This theoretical implication – emerging from a very simple model – is more subtle than we are aware of having previously been considered in the empirical literature (e.g., Ashraf et al. 2013).

The above theoretical model leads to a number of hypotheses that are testable using the experimental design:

Hypothesis I— Prices influence beliefs about the uncertain benefits of the new technology, especially among those not previously exposed to the technology. That is, $\frac{\partial \pi}{\partial p} > 0$ and $\frac{\partial \rho}{\partial p} > 0$. This is an assumption of the model, motivated by previous literature discussed above (Judd and Riordan 1994, Ashraf et al. 2013, Deserranno 2014), which needs to be further tested.

Hypothesis II— The effect of prices on beliefs about technology benefits is nonlinear: When social learning provides evidence that qualitatively agrees with prior beliefs, then the effect of prices on beliefs is diminished, i.e. $\frac{\partial \rho}{\partial p} < \frac{\partial \pi}{\partial p}$. This is an implication of the model which we are not aware of having been tested in previous research.

Hypothesis III— Social learning (i.e. peer effects) should have both first- and second-order effects:

(III.a) The first-order effect is that social learning should cause higher adoption (relative to uninformed households) when usage among prior adopters is high, and lower adoption when prior usage is low. That is, the difference $\left[P_\rho(e,p) - P_\pi(p)\right]$ should in theory be positive for high e and negative for low e.

(III.b) The second-order effect is that social learning should lead to a greater price-elasticity of demand when observed usage provides more certainty in prior beliefs (Hypothesis II). That is, $|(\partial P_\pi/\partial p)/(p/P_\pi)| < \left|\left(\partial P_\rho/\partial p\right)/(p/P_\rho)\right|$ under these conditions.

II. Methods and Study Design

Study Area

The P3 study takes place in the Kassena-Nankana (K-N) Districts in Northern Ghana (Figure 3). The climate in this region is hot and arid, with one rainy season lasting from approximately May to October, and the vegetation is dominated by woody shrubs and grassland. Much of the land is used in subsistence agriculture, with millet as the dominant crop. Ghana has one of the highest deforestation rates in Africa with the country's forest an estimated quarter of its original size (Appiah-Gyapong et al. 2011).

Since 1993, the NHRC has conducted a district-wide Health and Demographic Surveillance Survey (HDSS) (Oduro et al. 2012). According to HDSS data, the total population of the district is about 156,000 (roughly 30,000 households), with about 80% living in areas classified as rural while 20% are in more urban areas, primarily in and around the central town of Navrongo. Eighty eight percent of rural households report using biomass (wood or agricultural waste) as their main cooking fuel, while another 9% rely primarily on charcoal, and only about 3% of households cook primarily with gas or electricity. The traditional cooking method in these rural areas is a three-stone open fire, with many households also using charcoal stoves. Cooking is done both indoors and outdoors.

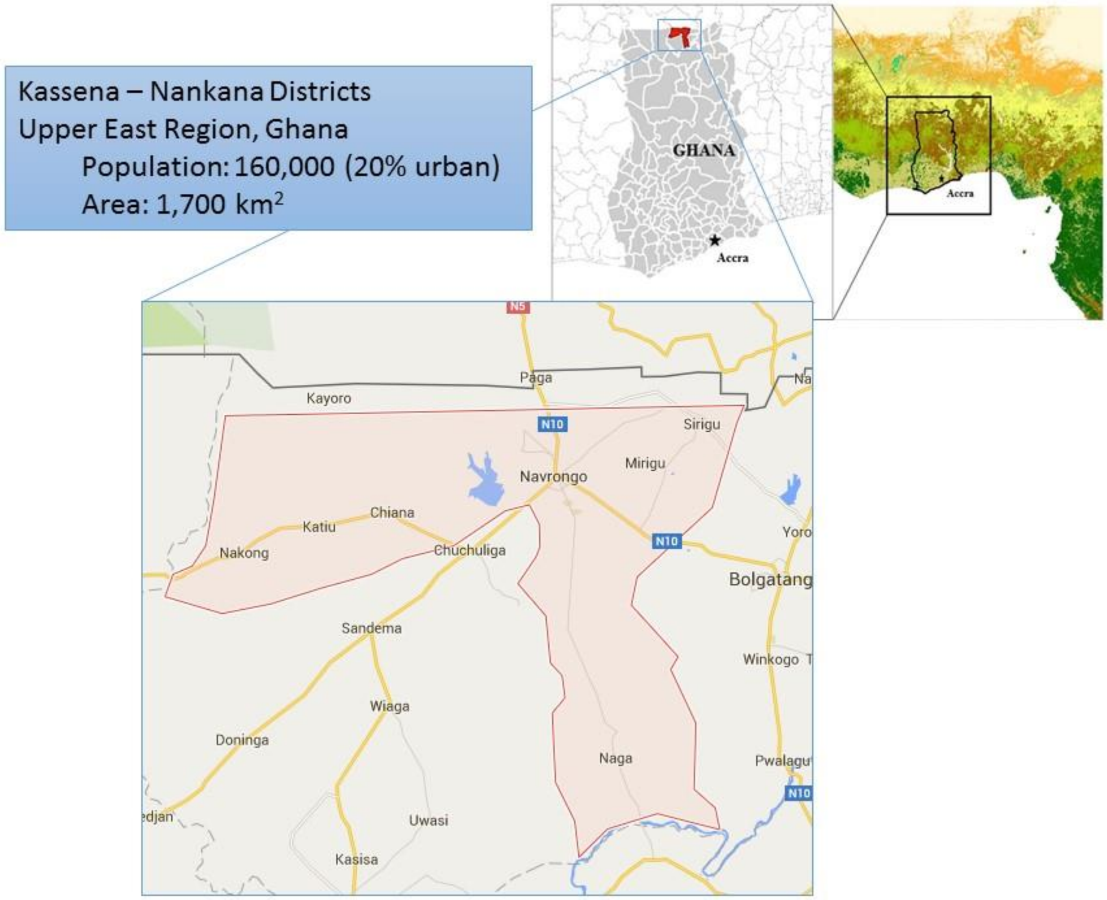

Figure 3: Map of the study area

Prior Research: The REACCTING Study

The P3 project builds on an earlier project, the Research of Emissions, Air Quality, Climate, and Cooking Technologies in Northern Ghana (REACCTING) study (Dickinson et al. 2015). The primary objective of the REACCTING study was to assess the effectiveness, feasibility, and sustainability of scaling up use of improved cookstoves in Northern Ghana through a coupled natural-human systems approach. For the purposes of the P3 project, the key feature of the REACCTING study was a randomized household-level intervention which distributed two types of improved biomass stoves for free to 200 participating households in the rural areas of the K-N Districts. Based on extensive feedback from households in the K-N district that tested several stove models during a pilot phase (2012-2013), two different stove technologies were selected for the REACCTING intervention study: the Gyapa Woodstove and the Philips Smokeless Woodstove (HD4012). The Gyapa Woodstove was specifically designed for use by populations in the Northern Regions of Ghana by Relief International/Gyapa Enterprises (RI/Gyapa). A similar model was used in a past intervention study in Accra, and saw significant decreases in kitchen carbon monoxide and particulate matter levels (Pennise et al. 2009). This model includes a combustion chamber, often called a rocket-stove design, with a ceramic liner on the inside and an outer liner of insulation and saw dust to increase heat retention. Meanwhile, the Philips stove was a gasifier stove produced in Lesotho. This stove was visually perceived as "high-tech," required power (supplied, in our context, through a small solar panel) to perform properly, and had been observed to be a low emitting technology, Tier 3 stove, during lab testing (Jetter et al. 2012).

The target population for the REACCTING intervention study was rural households in the K-N District that used biofuels (wood, animal waste, and crop residue) as their main cooking fuel source, and that contained women and young children (demographic groups typically in closest proximity to cooking activities). Data from the HDSS enabled a cluster random selection of households from the district population that met the REACCTING eligibility criteria. The social structure in this region is such that groups of related households live in connected compounds. For the purposes of the HDSS, compounds are grouped into geographic clusters. These clusters are grouped into five geographic regions: four of these are primarily rural (North, East, South, and West), while the Central region contains Navrongo town and surrounding areas. For the REACCTING sample, we first eliminated households from the Central region, and then randomly selected 25 clusters using population weighting to determine the number of clusters selected per region. Within each cluster, eight households were randomly selected from the population of households that met the study eligibility criteria, resulting in a total sample of 200 households.

The stove intervention of the REACCTING study included four different intervention arms: Group A received two Gyapa stoves, Group B received two Philips stoves, Group C received one of each type of stove, and Group D served as the control for the duration of the study and received two stoves of their choice at the study's conclusion. Stove stacking (i.e., households using new cookstoves alongside traditional cooking methods) had been observed in prior studies and we had earlier observed multiple stove use by the households in the study area. Multiple stoves were provided to each intervention household to increase the probability that households would begin to substitute away from traditional stoves rather than simply adding a new stove to their cooking technology mix. Randomization into intervention groups was done at the cluster level: i.e., within each of the 25 clusters, there are 2 households in each of the 4 REACCTING intervention groups. Stove distribution for the three intervention arms (A-C) occurred in December of 2013 and January of 2014. The control group (D) received their stoves in mid-2016.

P3 Intervention Design

To investigate how prices, peers, and perceptions affect adoption of improved cookstoves, our study leverages the fact that the REACCTING study's free distribution of stoves to randomly selected households provides *peers* of these households with information about these new technologies. Building on this prior work, the P3 study offers new stoves at *different price levels* to groups of households *with and without social ties* to the households that received stoves as part of this prior study. Through these experiments, **we will be able to identify the interacting feedbacks between prices and peer effects on perceptions** of stoves, as well as adoption and use outcomes across different groups.

Stove Selection

The design of our intervention requires that we offer stoves that are similar to those offered for the REACCTING study, since we are measuring whether learning about these technologies through peers influences adoption decisions. However, our experience in the REACCTING study revealed some key challenges with the two specific stove models used in that study (the Gyapa rocket stove and Philips forced draft stove). We thus elected to use slightly different stove models for the P3 project. A review of available technologies and consultation with manufacturers led us to select the ACE1 forced draft stove as a replacement for the Philips. Similar consultations and lab testing at CU Boulder allowed us to narrow our rocket stove options down to two: the Greenway Jumbo and EcoZoom Dura. A focus group discussion was conducted in September 2016 with participants similar to our target customers to compare and assess preferences for these two models. During the FGD, the team demonstrated the use of these stoves to participants. Participants were then divided into groups and given the necessary ingredients/materials to use the stoves to cook a common dish (jollof rice). Participants gave positive feedback on both stoves, but expressed a slight preference for the Greenway Jumbo. Since this stove also performed well in our lab testing, we subsequently selected this one for our intervention.

Sample Selection

The study design is summarized in Figure 4. For the purposes of this design, we refer to the REACCTING study sample as the R Group. Newly enrolled households that are the primary focus of this study, are referred to as the P3 Group. Our two phase sample selection procedure involves selecting clusters, and then selecting households within each cluster. In the first phase, the **PEER** subgroup was selected to include the same clusters as the R Group households (25 clusters), while the **NON-PEER** subgroup consists of 25 clusters randomly selected from the rural areas of the K-N Districts outside of a certain buffer distance from the R Group clusters. Given that there are more than 300 clusters in the district and only 25 were included in the R Group, social ties between NON-PEER and R Group households are expected to be minimal (and are measured as part of our data collection).

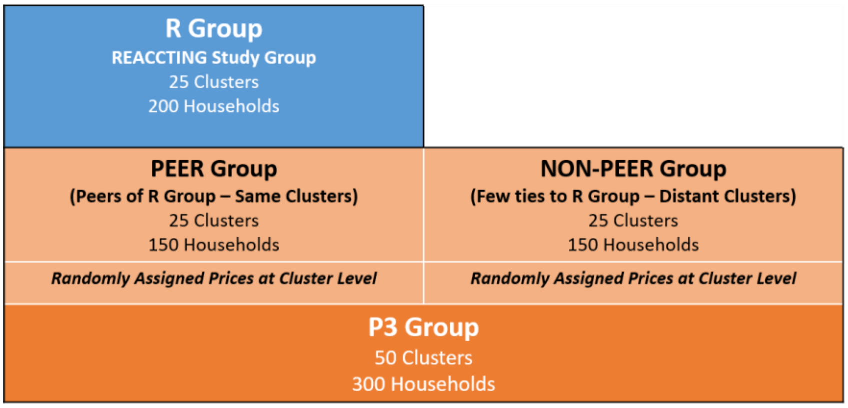

Figure 4: Study design

Next, the required number of households was selected from each cluster. We used the same inclusion and exclusion criteria used to select households in the REACCTING study (i.e., rural, using biofuel, having one woman 18-55 and one child under 5). PEER group households were selected as *nearest eligible neighbors* of each of the 6 REACCTING intervention households in each cluster. In the non-peer clusters, 6 seed households meeting the above eligibility criteria were randomly selected, and then non-peer group households were selected as the nearest neighbors of those seed households.

By using a uniform set of selection criteria and sampling methods between the PEER and NON-PEER groups, and given that both the R/PEER group and the NON-PEER group clusters were randomly selected, the study design ensures that in expectation the only differences between PEER and NON-PEER group households is the former's higher level of contact with peers that have cookstove experience, enabling us to test the impacts of this exposure on our outcomes of interest (perceptions and technology adoption and use).

Baseline Household Survey

For all 300 household participants, we conducted a comprehensive baseline survey between Dec 2016 and Feb 2017. This survey measured household composition and demographics, attitudes and priorities, cooking behaviors (including type(s) of stoves used, fuel use, foods cooked, who cooks within household), knowledge and perceptions of issues related to cooking practices, demand for new stoves, and self-reported health measures. In each household, the primary cook (typically female, aged 18-55 years old) served as the main survey respondent. In households where another male household member makes financial decisions, we also conducted a secondary survey with this individual. All baseline and follow up surveys are conducted using electronic tablets and the Open Data Kit (ODK) software.

Setting stove prices and randomizing across clusters

The experimental design for this intervention involves selecting price levels for the two stoves and distributing these prices across the peer and non-peer clusters. These price levels are set with the aim of maximizing the statistical precision of estimated economic demand for the stoves. The design procedure adopts methods from the economic discrete choice experiment (DCE) literature, to select price levels which maximize the D-efficiency criterion (Kanninen 2002). This methods follows the standard principle of seeking a set of experimental treatments which minimize the asymptotic covariance of the treatment effect estimates given a fixed sample size. We base our D-efficiency design on a conditional logit model (Lazari and Anderson 1994, Ferrini and Scarpa 2007), in which the probability of an experimental subject selecting stove j from a choice set t is:

$$p_{j|t}(\beta) = \frac{\exp \beta x_j}{\sum_{k \in J} \exp \beta x_k}$$

where x_j is a column vector of the stove's K attributes (in our application, price and the stove model) and β are regression coefficients to be estimated. D-efficiency seeks to identify a series of choice sets $t = 1, \ldots, T$ that minimize the expected asymptotic variance of maximum-likelihood estimate (MLE), β_{MLE}. The asymptotic variance of the MLE is inversely proportional to the Fischer information matrix, which in the conditional logit model with T choice sets compromised of A alternatives each is:

$$\mathcal{I}(\beta|\mathcal{X}) = \sum_{t=1}^{T} X_t' \left[\operatorname{diag}\big(\boldsymbol{p}_t(\beta, X_t)\big) - \boldsymbol{p}_t(\beta, X_t)' \boldsymbol{p}_t(\beta, X_t)\ \right] X_t$$

where X_t is the $K \times A$ matrix of attributes of each alternative in choice set t, $\mathcal{X}$ is the collection of these matrices over all T choice sets, and $\boldsymbol{p}_t(\beta, X_t)$ is the $1 \times A$ vector of conditional logit predicted probabilities given regression estimates β and attributes X_t.[1] The D-efficiency objective is to find a collection $\mathcal{X}$ of alternatives and attributes which maximize the determinant of $\mathcal{I}(\beta_{MLE}|\mathcal{X})$. In practice, β_{MLE} is not known a priori, and so an initial guess β_0 is used in experimental design.

Estimates of WTP came from two primary sources. First, during the REACCTING study, we measured participants' WTP for improved stoves at multiple time points. During the study's baseline survey, a choice experiment was conducted to assess stated WTP for hypothetical stoves with different attributes (e.g., less smoke, faster cooking time relative to traditional stoves). These stated WTP values were quite high; for example, average WTP for stoves that produced less smoke was on the order of 200 GHC (~USD$50) (Dickinson et al. 2014).

Due to concerns that these stated WTP values may have been larger than households' true willingness and ability to pay for improved stoves in this area, we decided to collect revealed preference information on WTP during the P3 design phase. Specifically, in November of 2015 we conducted a series of five focus group discussions in which we conducted a 2nd price, sealed-bid auction of different stove models with auction participants. Under classical economic assumptions, participants should bid their true ex ante WTP for the good (Krishna 2009). We auctioned one "mid/low-quality" stove – the Gyapa stove used in the REACCTING study – and two "high-quality" stove models – the ACE and the

[1] In matrix notation, the $\operatorname{diag}(x)$ function of a vector x forms a square matrix with the elements of x along the diagonal and zeros everywhere else, and X' denotes the transpose of X.

Philips. The bid data from these FGD auctions were used to provide some guidance on the range of households' WTP for different stove models. Results are discussed in Section 3.

Based on study resources, we decided that each household would be offered the option of purchasing up to two stoves consisting of any combination of the higher (ACE) and/or lower (Jumbo) quality stove models at prices randomly assigned to that household's cluster. Therefore, each choice set consisted of 6 alternatives (1-2 stoves of only one model, 1 of each model, or an opt-out), and the only components of $\mathcal{X}$ that were experimentally controlled were these price levels. Following standard practice, dominated alternatives were also eliminated from the design: in our case price configurations in which the lower-quality stove was sold at a higher price.

Implementation: Stove Orders

The intervention is being implemented by a local environmental NGO, the Organization for Indigenous Initiatives and Sustainability (ORGIIS), working closely with the NHRC and US-based researchers. Between March and May of 2017, ORGIIS and NHRC staff held a series of cluster-level meetings (6 households per cluster). For each participating household, both the primary cook and the financial decisionmaker (if these were not the same individual) were requested to attend the meeting. At these meetings, team members demonstrated the two types of stoves (Jumbo and ACE) and explained their benefits, and then provided participants the choice to purchase 0, 1, or 2 stoves (total) of either type at the cluster-randomized price levels. (Participants were informed that the stoves were being sold as part of a research study, and that participants in other areas may pay different prices for the stoves.)

During the meeting, the team explained that stoves would be ordered from international suppliers following the meeting, and delivered once they arrived (likely 2-3 months after orders were made). The payment arrangements were also explained: an initial deposit would be due at the time of stove delivery, with additional payments collected over the following six months. Once they were given all of this information, each household met individually with the study team to place their orders. After they finalized their choice, participants signed (or thumbprinted) a contract stating their commitment to purchase the selected stoves at the agreed upon price.

Follow-up Data Collection

Over the remaining duration of the P3 project, a variety of data collection activities will provide information on perceptions of stove quality and welfare impacts, stove adoption and use, and household air quality and exposure outcomes. First, after stove orders were made but before the recipients received their new stoves, we conducted a short follow up survey with all P3 Bio households to measure perceptions of the different types of stoves (Jun-Aug '17). Since our central research questions involve the roles of both prices and peers in shaping stove perceptions, these surveys provide important data on how participants perceive the different stoves and what benefits they expect to derive from them a priori.

Stoves were imported from manufacturers in Lesotho (ACE) and India (Jumbo) and arrived in Navrongo in late August 2017. ORGIIS subsequently delivered stoves to households and began collecting payments in September-October 2017. Data on stove payments (including refusals and defaults) will be collected over time.

Measurements of stove use (using electronic monitors), emissions, household air quality, and exposure, will be collected periodically for a subset of participants; all participants will complete an endline survey in Jul - Aug 2018.

Ethical Review
The study protocol was reviewed and approved by the Institutional Review Boards of the Navrongo Health Research Centre and the University of Colorado Boulder. Informed consent was obtained orally from all study participants prior to any data collection.

Data Analysis and Integration
In this paper, we present preliminary results based on the completed stove orders, as well as the baseline household survey. To analyze stove purchase outcomes, we estimate models of stove demand using discrete choice econometric methods (Train 2009), based on the experimental design described above. This analysis will be used first to statistically test the basic hypothesis that higher stove prices lead to lower demand for the stoves, all else equal (i.e. the 'Law of Demand' in economics). We also hypothesize that the higher-quality stoves will be in higher demand and that more of one or both stoves is weakly preferred, ceteris paribus.

After testing these basic hypotheses, we then examine between-cluster heterogeneity in stove demand to investigate a primary research question of this study: whether households in the PEER group have statistically different demand for stoves in the price experiments, compared to the NON-PEER group. Formally, this will be tested first by jointly estimating stove demand using conditional logit and other discrete choice models for both groups. By interacting an indicator for PEER group assignment with stove model and price coefficients in the regression analysis, we examine whether prior exposure affected demand by shifting it up or down, or by changing price elasticity (i.e. making the demand curve flatter or steeper). While assignment to the PEER group is random, by virtue of the previous REACCTING study, we also include household characteristics collected from surveys in these demand models, to improve statistical efficiency of the analysis.

III. Results

Household Sample Characteristics
Table 1 presents descriptive statistics for household characteristics, with tests for balance across the peer and non-peer groups. First, we examine household cooking practices at baseline. There is a growing consensus in the cookstove sector around the need to move beyond simply asking households to identify their *primary* cooking fuel, and instead to collect information on the full range of cooking fuels and stoves that households may rely upon. Thus, we asked about ownership and use of the three most common stoves that are found in the study area: three stone fires, charcoal stoves, and liquefied petroleum gas (LPG) stoves. The vast majority of households in our study have at least one three stone fire, and about 90% of households reported cooking on this type of stove on the day prior to the survey. Charcoal stoves, also known as "coal pots," are also quite common: about 70-75% of households had at least one coal pot, though less than a third of households reported using one of these "yesterday." In this rural sample, ownership and use of LPG stoves is rare. (In contrast, a companion project being conducted in the central urban area of the K-N District has found that about half of households in that area own LPG stoves (Dalaba et al. In review).) Cooking practices are well balanced across our peer and non-peer subgroups.

Next we turn to a set of location, demographic, and socioeconomic characteristics. On average, non-peer households are slightly farther from the central market in Navrongo town, though this difference is not statistically significant. In each household, surveys were administered to primary cooks; if another individual in the household was primarily in charge of financial decisions, that person was identified and interviewed as well. Across both peer and non-peer groups, roughly a quarter of primary cooks were also financial decisionmakers. Nearly all primary cooks were female. In cases where a second individual made financial decisions, that person was usually male. Primary cooks were typically in their late 30s, and the majority had less than a primary education. Households had about 7 members on average, and all but one household in the sample was engaged in farming. About a third of households had electricity.

Table 1: Descriptive Statistics for Household Sample

		Peer	Non-Peer	P-value*
# Households		149	144	
Cooking Practices				
Household has three stone stove		97.3%	97.2%	0.96
Household used three stone stove yesterday		90.6%	89.5%	0.76
Household has charcoal stove		69.8%	74.3%	0.39
Household used charcoal stove yesterday		26.9%	28.9%	0.70
Household has LPG stove		8.7%	6.3%	0.42
Household used LPG stove yesterday		2.1%	2.8%	0.66
Household Characteristics				
Distance to Navrongo market (m)	Mean	3664	4445	0.14
	SD	190	491	
Primary cook is financial decisionmaker		24.8%	22.9%	0.70
Primary cook gender: Female		97.3%	99.3%	0.19
Financial decisionmaker gender: Female		5.4%	2.7%	0.31
Primary cook age	Mean	38.0	40.2	0.15
	SD	1.0	1.1	
Primary cook education	Less than primary	73.8%	81.9%	0.23
	Primary / Junior High	20.1%	13.2%	
	Secondary or higher	6.0%	4.9%	
Household size	Mean	6.9	7.2	0.40
	SD	0.25	0.24	
Household engaged in farming		99.3%	100%	0.33
Household has electricity		34.2%	28.5%	0.29
Household has bank account		32.9%	24.3%	0.10
Household has mobile money		43.0%	29.9%	0.02
Household could borrow GHC2000		29.5%	40.3%	0.05
Peer/Stove Exposure				
Percent of seed contacts known	Mean	58.2%	56.1%	0.61
	SD	2.8%	2.9%	
Has seen Gyapa stove		85.2%	48.6%	0.00
Has seen Philips stove		41.6%	13.2%	0.00

**p-values are for tests of differences in proportions or means across peer and non-peer groups. For discrete variables, p-values are derived from chi-squared tests. For continuous variables, p-values are from t-tests.*

We see some evidence of an imbalance across peer and non-peer groups when we look at economic variables. Peer households were more likely to have a bank account and use mobile money services.

However, non-peer households were more likely to report that they would be able to borrow GHC 2000 (~US$500) if needed. As these economic variables may affect households' stove purchasing decisions, we will control for them in estimating stove demand models.

Finally, we are interested in assessing the degree of exposure that households had to peers in general, and specifically to peers that had used improved stoves in the REACCTING study. Recall that our sample selection process involved selecting nearest neighbors of certain seed households in each cluster. In the peer group, these were the eight households in each cluster that had participated in the REACCTING project and had received new stoves. In the non-peer clusters, these were simply randomly selected seed households. We asked each interviewed respondent whether or not they knew each of the seed households in their cluster. Contact with these potential peers was similar across groups: on average, respondents knew a little more than half of the seed households. This provides some evidence that general social network density was similar across groups.

Meanwhile, we find that households in the peer group were more likely to have heard of both types of improved stoves used in the REACCTING project. Interviewers showed respondents a photo of each stove and asked respondents if they had seen the stove before. About 85% of peer respondents recognized the lower-end Gyapa stove, compared to 49% of non-peer respondents. While this specific stove was not available in local markets, its design was similar to other woodstoves and charcoal stoves that were available in other areas of the country. The higher-end Philips stove was recognized by 42% of peer respondents and just 13% of non-peer respondents, reflecting the fact that this stove was more novel for this area. Overall, these statistics confirm that the peer and non-peer groups are fairly similar across most observable characteristics, while prior exposure to these improved stoves, which are very similar in design to those subsequently offered to these participants, is significantly higher in the peer group.

Stove Price Levels and Randomization

To design our intervention and maximize our ability to detect price and peer effects on stove choice, we needed prior data on willingness to pay for the Jumbo and ACE stove models. As a starting point, we used data from the five stove auctions that we conducted in November of 2015. The Gyapa stove (similar to the Jumbo) was auctioned in two of these meetings, while ACE stove were sold in two auctions and a Philips stove (similar to the ACE) was sold in the final auction. Results from these auctions are shown in Table 2. The mean bids for the higher quality stoves were 48% (Philips) and 84% (ACE) higher than for the Gyapa (Table 1). A quarter of participants in the higher-quality stove auctions bid at least 30 cedis, whereas only 5% of participants in the lower-quality stove auctions bid at least this amount (Figure 5).

Based on these results, we generated an initial set of prices for the two types of stove: GHC 0 to 30 for the Jumbo and GHC 0 to 60 for the ACE. After launching the sales experiment in the first four clusters in the North, we observed higher than expected stove demand. We therefore redesigned the price treatments again with the D-efficiency method for the remaining three levels based on this higher observed demand. For the final design, Jumbo stoves were sold for prices ranging from GHC 0 to 120 (~US$0 to $27), while the ACE was sold for GHC 15 to 240 (~US$3.50 to $55). This encompasses a range of prices from free-distribution to near 100% the cost of the stoves (US$30 for the Jumbo and $85 for the ACE).

Table 2: Bid information from stove auctions

Stove	Number of Bids	Bids			
		Ghanian cedis		US Dollars	
		Mean	Std. Dev.	Mean	Std. Dev.
Gyapa	31	13.10	8.19	$2.98	$1.86
Philips	23	19.35	16.88	$4.40	$3.84
ACE	27	24.04	25.25	$5.46	$5.74

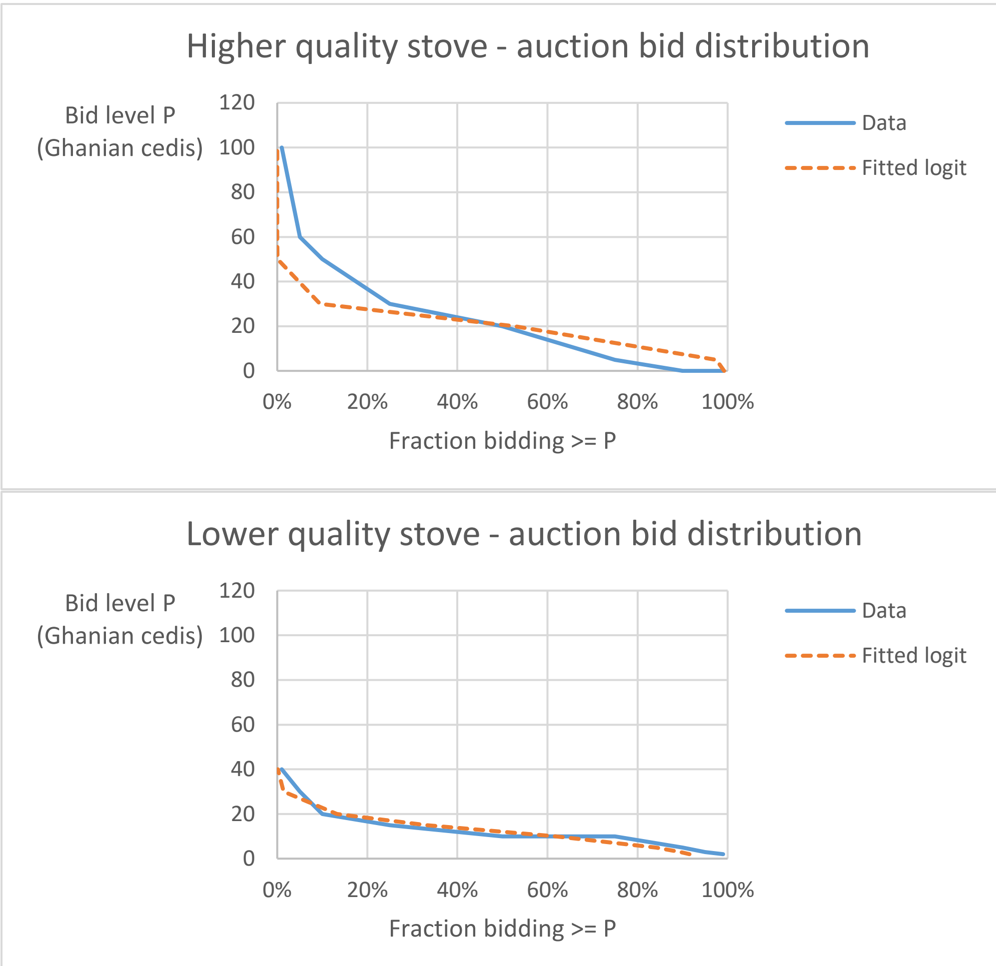

Figure 5: Distribution of bids for the higher quality (upper panel) and lower quality (lower panel) stoves in the stove auctions.

After generating the optimal set of price levels and their combinations, the next step involved randomly allocating across clusters and balancing these prices across peer and non-peer groups. Unfortunately, the study design team made an error in the process of generating these lists and transmitting the correct price levels to the field team for implementation. This resulted in an unequal distribution of prices between peers and non-peers (Figure 6). We emphasize that the source of this error clearly falls with the design team; the field team followed instructions and did not deviate from the price levels they were given. Thus, while the distribution of prices is not identical, prices were nonetheless randomly assigned and reasons for variation in price are not related to peer exposure. Thus, controlling for these observable price differences should still yield valid estimates of the effects of both prices and peers on stove demand.

Figure 6: Percent of households offered stoves at different price levels, by peer vs non-peer group. Top panel: Jumbo price levels. Bottom panel: ACE price levels.

Stove Orders and Demand Estimates

Stove order tallies are presented in Table 3. The first key observation from these results is that even with the higher prices that we introduced after the initial offers were made in the North clusters, demand for stoves appears quite high. Just 5.4% of peer group households and 2.1% of non-peers chose not to order any stoves, while about a quarter (22% of peers and 24% of non-peers) ordered one stove, and the majority (72% of peers and 74% of non-peers) chose one of the two stove combinations. The Jumbo-ACE combo was the dominant choice, selected by 65% of peers and 69% of non-peers.

To analyze stove choices and their determinants in more detail, we estimated a set of conditional logit models where the dependent variable is whether or not a particular stove package is chosen (Table 4). In the most basic model (Column 1), independent variables include total price of the package, indicators for whether the package includes a Jumbo / ACE stove, and an indicator for packages that include both stove types. In Columns 2 and 3, we estimate this same model separately for the peer group sample and the non-peer sample, respectively. Column 4 is run on the whole sample and includes interactions between peer group status and the package characteristics (price and stove type indicators). The final column adds interactions between price and three household covariates: whether the household has a mobile money account, respondent's age, and distance to the Navrongo market.

Table 3: Stove orders by Peer and Non-Peer Groups and Region

	Peer			**Non-Peer**		
Stove Order:	**North**	**Other regions**	**Total**	**North**	**Other regions**	**Total**
	N=36	N=113	N=149	N=36	N=108	N=144
No stoves	0%	7.1%	5.4%	0%	2.8%	2.1%
1 Jumbo	11.1%	8.9%	9.4%	2.8%	12.0%	9.7%
1 ACE	2.8%	15.9%	12.8%	11.1%	15.7%	14.6%
2 Jumbos	0%	0.88%	0.7%	0%	0.93%	0.7%
2 ACE	8.3%	5.3%	6.0%	2.8%	3.7%	3.5%
1 Jumbo, 1 ACE	75.0%	62.0%	65.1%	83.3%	64.8%	69.4%

Table 4: Conditional logit estimates for determinants of stove

VARIABLES	(1) Whole Sample	(2) Peers Only	(3) Non-Peers Only	(4) Whole Sample	(5) Whole Sample
Price	-0.0093***	-0.0086***	-0.011***	-0.011***	-0.023***
	(0.0020)	(0.0020)	(0.0025)	(0.0025)	(0.0065)
Jumbo	1.12**	0.78	1.79***	1.79***	2.14***
	(0.47)	(0.48)	(0.67)	(0.67)	(0.71)
ACE	2.81***	2.18***	3.98***	3.98***	4.43***
	(0.56)	(0.57)	(0.85)	(0.85)	(0.93)
PriceXPeer				0.0026	0.0023
				(0.0032)	(0.0033)
ACExJumbo	1.07*	1.38***	0.47	0.47	0.039
	(0.55)	(0.50)	(0.68)	(0.68)	(0.71)
JumboxPeer				-1.01	-1.27
				(0.82)	(0.85)
ACExPeer				-1.80*	-2.12**
				(1.03)	(1.08)
ACExJumboxPeer				0.91	1.25
				(0.84)	(0.87)
PriceXMobileMoney					0.0022
					(0.0018)
PriceXRespAge					-0.00010*
					(0.000058)
PriceXMktDist					0.0019***
					(0.00068)
Observations	1,752	888	864	1,752	1,686

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Across these models, price has the expected negative sign. CoefficientS for both of the individual stove type indicators are consistently positive, though the ACE coefficient is about 2-3 times as large as the Jumbo coefficient. In most models, the ACExJumbo interaction is also positive and significant, indicating that respondents perceived additional value to having these two stoves in combination. When the basic model is run separately for the peer and non-peer groups, there are three notable differences. The Jumbo coefficient is smaller and not statistically significant in the peer group, while the ACE coefficient is nearly twice as large in the non-peer group, and the ACExJumbo interaction is not significant in the non-peer group. This provides suggestive evidence of differences in demand for stove packages across these groups: peers appeared to see less value in each of the stoves individually, but had higher demand for the combination package. When peer interaction terms are included in the full model, we find that peer households had significantly lower demand for ACE stoves; the Jumbo interaction is also negative, and the ACExJumbo interaction is positive, though neither of these terms are statistically significant in these models.

Turning to covariates, access to a mobile money account does not have a significant effect on price elasticity of demand. The respondent age interaction is negative and significant, indicating that older respondents had more price elastic demand. Finally, the market distance interaction is positive and significant, suggesting that more remote households tended to have less price elastic demand for stove packages.

Estimated willingness to pay values from the basic model (Column 1) indicate that, on average, households were willing to pay US$27 (GHC120) for one Jumbo stove (95% confidence interval: US$4 to $50), US$68 for one ACE stove (95% confidence interval: US$41 to $96), and an additional US$26 for a package that combined the two types of stoves (95% confidence interval: US-$3 to $55). This implies an average WTP for the combination stove package of about US$97. We emphasize that these analyses are preliminary and the project is still in progress. Importantly, these analyses look at households' initial stove orders, rather than final purchasing and payment information. To the extent that some households refuse stoves at the time of delivery or fail to make all their payments, final willingness to pay estimates may be lower than what we report here.

IV. Discussion

There are several key observations from our preliminary results. First, these stove orders imply willingness to pay values for improved stoves that are somewhat surprising, for three reasons. First, prior studies have found low WTP for improved stoves in other contexts (Hanna et al. 2012, Mobarak et al. 2012). Second, while Ghana as a whole was classified as a middle income country starting in 2012, poverty rates remain high the Northern region where this study, particularly in rural areas. Results from the REACCTING study estimated average annual household expenditure in this population at roughly GHC2000 (US$450) per year. The expressed WTP for the combination stove package of US$97 thus represents about 20% percent of total annual expenditures. Third, our own formative research using stove auctions in this same population generated WTP estimates that lower than those presented here by about an order of magnitude. Possible reasons for the difference between auctions and these take-it-or-leave-it offers include misunderstanding of the auction rules among participants, leading them to submit bids lower than their true maximum WTP, and the fact that in the auctions, the first payments were due immediately (that day), rather than at a date 1-2 months in the future. (The repayment period of six months was the same for auction winners.)

Interestingly, our observed WTP values are more closely aligned with stated preference estimates from the REACCTING project. During the baseline (pre-intervention) survey for that project, a choice experiment was conducted to measure WTP for hypothetical stoves with different attributes (e.g., less smoke, fuel savings, faster cooking time relative to traditional stoves) (Dickinson et al. 2014). Average

WTP for stoves that produced less smoke was on the order of 200 GHC (~USD$50). These values were considered quite high at the time, prompting us to undertake a revealed preference approach (the auctions) to generate more plausible WTP priors for the P3 intervention. The similarity between the REACCTING stated preference estimates and estimates derived from the stove order data is thus striking.

Another key factor likely affecting willingness to pay in this experiment involves the payment structure and timing. Households committed to purchasing stoves with the expectation that they would receive them and make a first payment in about 2 months, with the remaining payments made over the following six month period. Thus, payments were somewhat temporally distant at the time stoves were ordered. If households had high discount rates, this could lead these future payments to appear smaller, leading to higher demand. The question, then, is whether households will follow through on their commitments. Initial reports from the study team indicate that of 282 households that ordered at least one stove, 260 made an initial deposit and received their stoves between September and October of 2017. Additional installments are currently being collected; households that fail to make all payments within six months of receiving their stoves will be required to return their stoves to the project team at that time, with any payments made returned to the household.

Turning to our peer effects, initial results suggest interesting differences in demand for stove packages across groups. The overall pattern of results shows that peers may have lower demand for both types of stoves on their own, but somewhat higher demand for the package that included one of each type of stove. In the REACCTING study, the three intervention groups were randomly assigned a combination of two stoves, while the control group was able to select which stove combination they received at the end of the study. This choice was made about 18 months after the study began, such that the experience of intervention group households likely played a role in the control group's choices. For these households, the control group package was the dominant choice; 34 of 48 households (71%) selected this option, while 8 (17%) chose two Philips (high-end) stoves and 6 (13%) chose two Gyapa (lower-end) stoves. Thus, P3 peer group households' preference for the stove combination is similar to the revealed preferences of the REACCTING control group. Combined with the fact that P3 peers also reported more familiarity with improved stoves, we find initial evidence that learning about these stoves from the REACCTING participants may have shaped P3 participants' stove choices.

Analyses of follow up data on several key outcomes will shed additional light on the interactive effects of prices, peers, and perceptions on technology adoption in this context. Data on stove deliveries, payments, refusals, and defaults will allow us to update willingness to pay estimates, and assess to what extent households overstated their true willingness and ability to pay for these stoves when they made their orders. We will also assess how these adjusted WTP values and adoption outcomes vary between peer and non-peer groups. Data on stove use – collected through the endline survey in all households as well as through electronic stove use monitors in a subset of homes – will allow us to revisit questions about the relationship between price and technology use, and whether peer effects are present here as well. We will also assess how stove perceptions – a key piece of the technology adoption puzzle that has not been measured extensively in prior work – vary across groups and over time, and how this variation relates to subsequent behaviors and choices (orders, payments, defaults, and stove use). Finally, a unique feature of the P3 project is our interdisciplinary research team, which includes environmental economists, health researchers, and engineers specializing in cutting-edge methods to measure stove emissions, household air quality, and personal exposure. Taken together, these results will shed light on the complex problem of improved stove technology adoption and its impacts, informing subsequent research and practice.

V. References

Ali, M. M., J. Cleland and I. H. Shah (2004). "Condom use within marriage: a neglected HIV intervention." Bulletin of the World Health Organization **82**(3): 180-186.

Anthony, J. (2010). "Secretary Clinton Announces Global Alliance for Clean Cookstoves." Global Alliance for Clean Cookstoves, from http://www.cleancookstoves.org/media-and-events/press/secretary-clinton-announces.html.

Ashraf, N., B. K. Jack and E. Kamenica (2013). "Information and subsidies: Complements or substitutes?" Journal of Economic Behavior & Organization **88**: 133-139.

Bagwell, K. and M. H. Riordan (1991). "High and declining prices signal product quality." The American Economic Review: 224-239.

Blackden, C. M. and Q. Wodon (2006). Gender, time use, and poverty in sub-Saharan Africa, World Bank Publications.

Bobonis, G. J. and F. Finan (2009). "Neighborhood peer effects in secondary school enrollment decisions." Review of Economics and Statistics **91**(4): 695-716.

Bollinger, B. and K. Gillingham (2012). "Peer Effects in the Diffusion of Solar Photovoltaic Panels Peer Effects in the Diffusion of Solar Photovoltaic Panels." Marketing Science **31**(6): 900-912.

Bond, T. C., D. G. Streets, K. F. Yarber, S. M. Nelson, J. H. Woo and Z. Klimont (2004). "A technology-based global inventory of black and organic carbon emissions from combustion." Journal of Geophysical Research: Atmospheres (1984–2012) **109**(D14).

Cohen, J. and P. Dupas (2010). "Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment*." Quarterly Journal of Economics **125**(1): 1.

Conley, T. and C. Udry (2010). "Learning about a new technology: Pineapple in Ghana." American Economic Review **100**(1): 35-69.

Dalaba, M., R. Alirigia, E. Mesenbring, E. Coffey, Z. Brown, M. Hannigan, C. Wiedinmyer, A. Oduro and K. Dickinson (In review). "Supply and Demand of Liquefied Petroleum Gas (LPG) for Cooking in Northern Ghana." EcoHealth.

Deserranno, E. (2014). Financial Incentives as Signals: Experimental Evidence from the Recruitment of Health Workers.

Dickinson, K. and S. K. Pattanayak (2008). Open sky latrines: Do social interactions influence decisions to use toilets? Madison, WI, University of Wisconsin.

Dickinson, K. L., Y.-Y. Hsu, E. Kanyomse and A. R. Oduro (2014). "Where There's Smoke…: Measuring Preferences for Improved Cookstove Attributes using Choice Experiments in Northern Ghana." In preparation.

Dickinson, K. L., E. Kanyomse, R. Piedrahita, E. Coffey, I. Rivera, J. Adoctor, R. Aligiria, D. Muvandimwe, M. Dove, V. Dukić, M. Hayden, D. Diaz-Sanchez, V. Adoctor, D. Anaseba, Y. C.-H. Slichter, N. Masson, A. Monaghan, A. Titiati, D. Steinhoff, Y.-Y. Hsu, R. Kaspar, B. Brooks, A. Hodgson, M. Hannigan, A. R. Oduro and C. Wiedinmyer (2015). "Research on Emissions, Air quality, Climate, and Cooking Technologies in Northern Ghana (REACCTING): Study Rationale and Protocol." BMC Public Health **15**: 126.

Dupas, P. (2014). "Getting essential health products to their end users: Subsidize, but how much?" Science **345**(6202): 1279-1281.

Ezzati, M. and D. M. Kammen (2001). "Indoor air pollution from biomass combustion and acute respiratory infections in Kenya: an exposure-response study." The Lancet **358**(9282): 619-624.

Ferrini, S. and R. Scarpa (2007). "Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study." Journal of Environmental Economics and Management **53**(3): 342-363.

Hanna, R., E. Duflo and M. Greenstone (2012). Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves, National Bureau of Economic Research.
Jetter, J., Y. Zhao, K. R. Smith, B. Khan, T. Yelverton, P. DeCarlo and M. D. Hays (2012). "Pollutant Emissions and Energy Efficiency under Controlled Conditions for Household Biomass Cookstoves and Implications for Metrics Useful in Setting International Test Standards." Environmental Science & Technology **46**(19): 10827-10834.
Judd, K. L. and M. H. Riordan (1994). "Product Quality in a New Monopoly." Review of Economic Studies **61**(4): 773-789.
Kahneman, D. and A. Tversky (1979). "Prospect theory: An analysis of decision under risk." Econometrica: Journal of the Econometric Society: 263-291.
Kanninen, B. J. (2002). "Optimal design for multinomial choice experiments." Journal of Marketing Research **39**(2): 214-227.
Kremer, M. and E. Miguel (2007). "The illusion of sustainability." Quarterly Journal of Economics **122**(3): 1007-1065.
Krishna, V. (2009). Auction theory, Academic press.
Lazari, A. G. and D. A. Anderson (1994). "Designs of Discrete Choice Set Experiments for Estimating Both Attribute and Availability Cross Effects." Journal of Marketing Research **31**(3): 375-383.
Lim, S. S., T. Vos, A. D. Flaxman, G. Danaei, K. Shibuya, H. Adair-Rohani, M. A. AlMazroa, M. Amann, H. R. Anderson, K. G. Andrews, M. Aryee, C. Atkinson, L. J. Bacchus, A. N. Bahalim, K. Balakrishnan, J. Balmes, S. Barker-Collo, A. Baxter, M. L. Bell, J. D. Blore, F. Blyth, C. Bonner, G. Borges, R. Bourne, M. Boussinesq, M. Brauer, P. Brooks, N. G. Bruce, B. Brunekreef, C. Bryan-Hancock, C. Bucello, R. Buchbinder, F. Bull, R. T. Burnett, T. E. Byers, B. Calabria, J. Carapetis, E. Carnahan, Z. Chafe, F. Charlson, H. Chen, J. S. Chen, A. T.-A. Cheng, J. C. Child, A. Cohen, K. E. Colson, B. C. Cowie, S. Darby, S. Darling, A. Davis, L. Degenhardt, F. Dentener, D. C. Des Jarlais, K. Devries, M. Dherani, E. L. Ding, E. R. Dorsey, T. Driscoll, K. Edmond, S. E. Ali, R. E. Engell, P. J. Erwin, S. Fahimi, G. Falder, F. Farzadfar, A. Ferrari, M. M. Finucane, S. Flaxman, F. G. R. Fowkes, G. Freedman, M. K. Freeman, E. Gakidou, S. Ghosh, E. Giovannucci, G. Gmel, K. Graham, R. Grainger, B. Grant, D. Gunnell, H. R. Gutierrez, W. Hall, H. W. Hoek, A. Hogan, H. D. Hosgood Iii, D. Hoy, H. Hu, B. J. Hubbell, S. J. Hutchings, S. E. Ibeanusi, G. L. Jacklyn, R. Jasrasaria, J. B. Jonas, H. Kan, J. A. Kanis, N. Kassebaum, N. Kawakami, Y.-H. Khang, S. Khatibzadeh, J.-P. Khoo, C. Kok, F. Laden, R. Lalloo, Q. Lan, T. Lathlean, J. L. Leasher, J. Leigh, Y. Li, J. K. Lin, S. E. Lipshultz, S. London, R. Lozano, Y. Lu, J. Mak, R. Malekzadeh, L. Mallinger, W. Marcenes, L. March, R. Marks, R. Martin, P. McGale, J. McGrath, S. Mehta, Z. A. Memish, G. A. Mensah, T. R. Merriman, R. Micha, C. Michaud, V. Mishra, K. M. Hanafiah, A. A. Mokdad, L. Morawska, D. Mozaffarian, T. Murphy, M. Naghavi, B. Neal, P. K. Nelson, J. M. Nolla, R. Norman, C. Olives, S. B. Omer, J. Orchard, R. Osborne, B. Ostro, A. Page, K. D. Pandey, C. D. H. Parry, E. Passmore, J. Patra, N. Pearce, P. M. Pelizzari, M. Petzold, M. R. Phillips, D. Pope, C. A. Pope Iii, J. Powles, M. Rao, H. Razavi, E. A. Rehfuess, J. T. Rehm, B. Ritz, F. P. Rivara, T. Roberts, C. Robinson, J. A. Rodriguez-Portales, I. Romieu, R. Room, L. C. Rosenfeld, A. Roy, L. Rushton, J. A. Salomon, U. Sampson, L. Sanchez-Riera, E. Sanman, A. Sapkota, S. Seedat, P. Shi, K. Shield, R. Shivakoti, G. M. Singh, D. A. Sleet, E. Smith, K. R. Smith, N. J. C. Stapelberg, K. Steenland, H. Stöckl, L. J. Stovner, K. Straif, L. Straney, G. D. Thurston, J. H. Tran, R. Van Dingenen, A. van Donkelaar, J. L. Veerman, L. Vijayakumar, R. Weintraub, M. M. Weissman, R. A. White, H. Whiteford, S. T. Wiersma, J. D. Wilkinson, H. C. Williams, W. Williams, N. Wilson, A. D. Woolf, P. Yip, J. M. Zielinski, A. D. Lopez, C. J. L. Murray and M. Ezzati (2012). "A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010." The Lancet **380**(9859): 2224-2260.
Manski, C. F. (1993). "Identification of endogenous social effects: The reflection problem." Review of Economic Studies **60**(3): 531-542.

McFadden, D. (1974). "Conditional Logit Analysis of Qualitative Choice Behavior." Frontiers in Econometrics: 105-142.
Milgrom, P. (1981). "Good news and bad news : representation theorems and applications." The Bell Journal of Economics **12**(2): 380-391.
Miller, G. and A. M. Mobarak (2013). Learning about New Technologies through Opinion Leaders and Social Networks: Experimental Evidence on Non-Traditional Stoves in Rural Bangladesh, Poverty Action.
Mobarak, A. M., P. Dwivedi, R. Bailis, L. Hildemann and G. Miller (2012). "Low demand for nontraditional cookstove technologies." Proceedings of the National Academy of Sciences **109**(27): 10815-10820.
Mobarak, A. M., P. Dwivedi, R. Bailis, L. Hildemann and G. Miller (2012). "Low demand for nontraditional cookstove technologies." Proceedings of the National Academy of Sciences of the United States of America **109**(27): 10815-10820.
Oduro, A. R., G. Wak, D. Azongo, C. Debpuur, P. Wontuo, F. Kondayire, P. Welaga, A. Bawah, A. Nazzar and J. Williams (2012). "Profile of the navrongo health and demographic surveillance system." International journal of epidemiology **41**(4): 968-976.
Pattanayak, S. K., J. Blitstein, J. C. Yang, S. R. Patil, K. M. Jones, C. Poulos and K. L. Dickinson (2006). Evaluating information and communication strategies to promote latrine use and improve child health: Design and baseline findings from a community randomized trial in Bhadrak, Orissa. RTI Working Paper. Research Triangle Park, North Carolina.
Pattanayak, S. K., J.-C. Yang, K. L. Dickinson, C. Poulos, S. R. Patil, R. Mallick, J. Blitstein and P. Praharaj (2009). "Shame or subsidy revisted: Randomized evaluation of social mobilization for sanitation in Orissa, India." Bulletin of the World Health Organization **87**(8): 580-587.
Smith-Sivertsen, T., E. Diaz, D. Pope, R. T. Lie, A. Diaz, J. McCracken, P. Bakke, B. Arana, K. R. Smith and N. Bruce (2009). "Effect of reducing indoor air pollution on women's respiratory symptoms and lung function: the RESPIRE Randomized Trial, Guatemala." American journal of epidemiology **170**(2): 211-220.
Smith, K. R. (1987). Biofuels, air pollution, and health: a global review. New York, NY, Plenum Press.
Smith, K. R. (2012). Letter to the Editor: Response to "Too many cookstoves spoil the effort to cut indoor air pollution". Washington Post. **April 18, 2012**.
Smith, K. R., N. Bruce, K. Balakrishnan, H. Adair-Rohani, J. Balmes, Z. Chafe, M. Dherani, H. D. Hosgood, S. Mehta and D. Pope (2014). "Millions dead: how do we know and what does it mean? Methods used in the Comparative Risk Assessment of Household Air Pollution." Annual review of public health **35**: 185-206.
Smith, K. R., J. P. McCracken, L. Thompson, R. Edwards, K. N. Shields, E. Canuz and N. Bruce (2009). "Personal child and mother carbon monoxide exposures and kitchen levels: methods and results from a randomized trial of woodfired chimney cookstoves in Guatemala (RESPIRE)." Journal of Exposure Science and Environmental Epidemiology **20**(5): 406-416.
Smith, K. R., S. Mehta and M. Maeusezahl-Feuz (2004). "Indoor air pollution from household use of solid fuels." Comparative quantification of health risks: global and regional burden of disease attributable to selected major risk factors **2**: 1435-1493.
Train, K. E. (2009). Discrete choice methods with simulation, Cambridge university press.
World Bank (2015). World Development Report 2015: Mind, Society, and Behavior. Washington D.C., World Bank Group.