Show and Tell: Causal Impacts of Field Days on Farmer Learning for Organic Inputs in Kenya

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Selected Paper prepared for presentation at the 2019 Agricultural & Applied Economics Association Annual Meeting, Atlanta, GA, July 21 – July 23

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Version Date: September 2, 2019

JEL Codes: Q12, O13, Q24, D83, C93

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Abstract: Farmer field days (FFDs) are a tool often used in developing countries to transfer knowledge about new agricultural technologies or methods from trained farmers to others in their communities. However, there has thus far been a lack of rigorous economic analysis of the effectiveness of FFDs for information diffusion. To fill this gap in the literature, we surveyed and conducted experimental auctions for agricultural inputs with a random sample of individuals from villages that held FFDs for novel organic inputs in western Kenya. We identify the relationship between attendance at a FFD and willingness to pay (WTP) for organic inputs through a spatial instrument using homestead and FFD locations. Following predictions from our model pointing to increased knowledge of risks and expected benefits of the new inputs, we find that attendance at a FFD significantly decreases WTP for organic inputs by 16% of the average input value and likewise decreases the WTP ratio for organic inputs relative to a common inorganic input by 12.3 percentage points compared to non-attendees. This study shows that FFDs can be effective in transmitting comprehensive information of new agricultural technologies to large numbers of individuals, and can be a useful tool to scale-up the impacts of more traditional extension programs in developing countries.

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Crop yields remain highly variable and far below potential in many developing countries, which is linked with significant levels of food insecurity and rural poverty (Barrett and Bevis, 2015; Frelat et al., 2016). For this reason, researchers have continued to seek the most effective means for diffusing information on agricultural technologies and practices that enhance farm productivity. A popular, yet oft-debated method is the "Farmer Field School" (FFS), a participatory approach that emphasizes discovery and self-learning on the part of farmers (FAO, 2011). Focusing on experiential and group learning, FFS can potentially lead to the adoption of new technologies and more effective agricultural methods, as well as increasing the capacity and confidence of participants − especially among women, poor, and minority farmers (FAO, 2011; Davis et al., 2012).

The introduction of FFS across developing countries reflected a paradigm shift in information transfer, in which the trainer facilitates self-discovery rather than simply serving as an instructor (Roling and van de Fliert, 1994; Feder, Murgai, and Quizon, 2004a). The earliest analyses of FFS programs come from integrated pest management (IPM) projects in southeast Asia (Feder, Murgai, and Quizon, 2004a,b; Tripp, Wijeratne, and Piyadasa, 2005; Van den Berg and Jiggins, 2007). Typically in these programs, farmers regularly meet with neighbors over the course of one or more cropping seasons to discuss, share, and analyze their agro-ecosystems, and test and evaluate new experimental IPM interventions (Van den Berg and Jiggins, 2007). This collective learning through FFS programs enables participants to gain confidence, expertise, and strengthens learning that can be carried over past the end of the program. FFS for other technologies and agricultural methods have since been expanded to areas such as East Africa, where Davis et al. (2012) show positive impacts of the programs on agricultural incomes and female empowerment. More recent studies have demonstrated that FFS can be effective in increasing agricultural knowledge (Bonan and Pagani, 2018), crop yields (Tsiboe et al., 2016), and food security (Larsen and Lilleor, 2014), though the latter study finds no effect on poverty reduction.

However, there does not exist consensus in the literature regarding the effectiveness of FFS, either in impact or cost, and caution is warranted. There are few studies that rigorously evaluate the outcomes of FFS, and many studies that do exist have questionable internal validity (Waddington et al., 2014). Moreover, Farmer field schools are relatively expensive, requiring training, monitoring, and evaluation over an extended period of time (Quizon, Feder, and Rinku, 2001). To prove cost effective, it is generally assumed that those trained in FFS will diffuse their knowledge to other farmers in their village. Evidence exists demonstrating that agricultural information can spread among individuals within the same village social network (Conley and Udry, 2010; Foster and Rosenzweig, 2010; Maertens and Barrett, 2013). Some recent literature has specifically examined the spread of technology from trained farmers to others in their network. Looking at five-year panel data from Tanzania, Nakano et al. (2018) found evidence of the diffusion of improved rice technology from trained primary farmers to other farmers in their villages, while Kondylis, Mueller, and Zhu (2017) show large positive effects from training contact farmers on community adoption rates of technology in Mozambique. In their survey of the FFS literature, however, Waddington et al. (2014) found limited evidence of diffusion of information from FFS farmers to other farmers in their village. Whether FFS in particular can catalyze the diffusion of information within developing countries is still an open question.

In the context of FFS, farmer field days (FFDs) can potentially aid in diffusing information from the trained FFS farmers to their communities. During FFDs, trained farmers hold on-farm events seeking to transfer information to their community in attendance (FAO, 2011). A farmer who, for example, had been trained in a FFS to use new agricultural inputs, will invite neighbors, other farmers, and local government officials to a one-day event to showcase the impacts of the input on his/her yields and teach attendees about the input. While FFDs do not include the advantages of long-term experiential and discussion-based learning found in the FFS itself, they can aid in the cost effectiveness of FFS programs through broadening the numbers of individuals exposed to the information in a particular area (Amudavi et al., 2009). Moreover, FFDs empower FFS participants by showcasing their accomplishments to the community and demonstrating to local government officials the benefits of new technologies/methodologies, which may increase future support (FAO, 2011).

While FFDs are often integral aspects of the FFS strategy that can multiply the FFS impacts throughout a community, there are few economic studies that have focused specifically on FFDs and their impact on information diffusion. One, by Ricker-Gilbert et al. (2008) in Bangladesh, find that FFDs are particularly cost effective as they can reach a large number of farmers for low cost. However, the general lack of rigorous studies analyzing the effectiveness of FFDs is notable given the large numbers of studies that focus on technology diffusion in developing countries (Foster and Rosenzweig, 2010; Magruder, 2018). To fill this gap in the literature, we analyze the impact of FFD activities on farmers' willingness to pay (WTP) for organic agricultural inputs in western Kenya. We measure WTP by conducting experimental auctions after Becker, DeGroot, and Marschak (1964) (BDM) for the organic inputs discussed at the FFD with a random sample of individuals from the villages (some of whom had attended a FFD). To causally identify the relationship between FFD attendance and WTP, we use the GPS-determined distance between a farmer's homestead and the FFD location (which, as we discuss later, is as good as random within a particular village).

Although following directly from our theoretical framework, we find a result that at first blush may seem surprising. Using 2SLS with village-level fixed effects and clustered standard errors, individuals who state that they attended the FFD bid almost 30 KSh (about 16% of average WTP) *less* for organic inputs than non-attendees. This is despite of most of organic input demonstration plots performing better than control plots on the same farm. We also find that the WTP ratio for organic inputs to DAP (diammonium phosphate – a common inorganic fertilizer) was 12.3 percentage points less among FFD attendees compared to non-attendees. We find even larger magnitudes of the effect on WTP when we measure knowledge of the inputs, rather than simply attendance at FFD. These results show that FFDs transmit information to farmers to an extent that cause a statistically significant and economically meaningful impact on farmer behavior.

To understand the mechanism for these effects, we use a theoretical framework adopted from studies that have highlighted the effects of information as influencing the distribution of WTP values (Johnson and Myatt, 2006; Rickard et al., 2011; Liaukonyte, Streletskaya, and Kaiser, 2015). Our model demonstrates that an information signal that updates farmer perceptions about an input's profitability can both shift and rotate the CDF and inverse demand curves. All farmers in our sample received a brief description of the organic inputs by the enumerators, while those who attended the FFD received significantly more detailed and varied information through visual inspection of demonstration plots and instruction from the host farmer The results of our study show that information provided by FFDs may have impacted WTP through 1) increasing the knowledge of benefits of risks associated with the input for particular soil types and nutrient levels (indeed, we find those who attended FFDs had better estimates of the inputs' values than non-attendees), and 2) increasing the precision of WTP estimates, decreasing the variance of its distribution.

This study also makes important contributions to the literature discussing cost-effective methods of information diffusion in developing countries. Traditional agricultural extension is relatively costly, and evidence has been mixed as to the efficacy of this system (Birkhaeuser, Evenson, and Feder, 1991; Anderson and Feder, 2004). However, because FFS are also expensive, there has been a search for alternative methods of information diffusion. This has ranged from using mobile phones to disseminate information (Aker, 2011), which many in rural areas of SSA now own, to using network analysis to target optimal entry points of information into social networks in order to maximize information diffusion from key farmers (Banerjee et al., 2013; Beaman et al., 2015). A significant literature has emerged analyzing the impacts of learning from fellow farmers in developing countries (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010; BenYishay and Mobarak, 2018).

Notably, learning from peers has been shown to be more effective than learning from extension agents (Krishnan and Patnam, 2013). Because research shows that social learning can be so effective for information diffusion, FFDs represent a potentially strong though understudied tool linking FFS with broader information dissemination through peer linkages.

This study is organized in the following way: we first discuss our theoretical framework, focusing on how information impacts the WTP distribution of FFD attendees and non-attendees. We next explore our data and the project background, which includes a discussion of our calculation of the value of the organic inputs used in the study. We then discuss our empirical method and identification strategy, focusing on our spatial instrument. Using that section as a guide, we then detail our results that show the significant impact of the FFDs on farmer WTP. Various robustness and falsification checks are next discussed, followed by our concluding remarks.

Theoretical Framework

To frame our analysis of the effects of FFDs on farmer WTP, we use a model after Johnson and Myatt (2006), Liaukonyte, Streletskaya, and Kaiser (2015) and Murphy et al. (2019) to analyze the effect of information on consumer demand. In our context, we have a new input k with profitability $\pi_k(E_k)$, where for simplicity we assume π_k is primarily a function of the unit increase in yields for a unit increase of the input applied per hectare (or agronomic efficiency) E (Vanlauwe et al., 2011).[1] Profitability for input k, π_k, is not constant, but varies by soil condition, rainfall, etc, and we assume a normal distribution for π_k defined by $N(\mu_k, \sigma_k^2)$. The variance σ^2 is small when the profitability of k is similar for all farmers, and large when there is significant heterogeneity in its profitability. Given the large degree of variation in soil nutrient levels in western Kenya, for many inputs, σ^2 is often large. Prior to any information received through a FFD or staff visit, for simplicity we assume that an

[1] We assume that in the western Kenyan context, these farmers are both consumers and producers. Zapata and Carpio (2014) show that a farmer's utility maximization is directly connected with his/her profit maximization.

individual i has a prior on μ and σ^2. A farmer receives an information signal, ω_k regarding the profitability of input k, where $\omega_k \sim N\left(\pi_k, \zeta_k^2\right)$.

In this study, there are two groups (g) of farmers: FFD attendees (A) and non-attendees (N); $g = \{A, N\}$. Those in each group receive different information signals, such that $\omega_{Ak} \neq \omega_{Nk}$. Importantly, we assume that the variance of the information signals to attendees, ω_{Ak}, is $\zeta_{Ak}^2(var(E_k))$, that is, a function of the variance of the agronomic efficiency of input k. This is because at FFDs, attendees receive complex information signals regarding the input's profitability, as this varies with its agronomic efficiency E (itself a function of soil nutrient levels and other site-specific conditions, which vary based on field day site). Indeed, as table 1 illustrates, there were heterogeneous effects of the organic inputs on FFD demonstration plot crop yields not only across field day sites, but within farms as well. The information signal for non-attendees, however, is simply the brief information provided to them at the time of the survey by the enumerators, such that ζ_{Nk}^2 is less dispersed and only a function of individual enumerator characteristics.

With Bayesian updating, a farmer's updated posterior of input profitability becomes:

$$\pi_k|\omega_{gk} \sim N\left(\frac{\sigma_k^2\omega_{gk} + \zeta_{gk}^2\mu_k}{\sigma_k^2 + \zeta_{gk}^2}, \frac{\sigma_k^2\zeta_{gk}^2}{\sigma_k^2 + \zeta_{gk}^2}\right) \tag{1}$$

If we assume that farmers are maximizing their utility under particular risk preferences, we can arrive at their WTP by inserting the results of equation 1 into a certainty equivalent $E[\pi_k|\omega_{gk}] - \lambda var[\pi_k|\omega_{gk}]/2$, where λ is a parameter indicating level of risk aversion (assumed, for simplicity, to be uniform across participants) (Featherstone and Moss, 1990):

$$\theta(\omega_{gk}) = \left[\mu_k\zeta_{gk}^2 + \sigma_k^2\omega_{gk} - \frac{\lambda\sigma_k^2\zeta_{gk}^2}{2}\right]\left(\sigma_k^2 + \zeta_{gk}^2\right)^{-1} \tag{2}$$

which we can see is weighted average of the original distribution of π_k and that of the information signal. If we assume that realized information signals are distributed $\omega_{gk} \sim N(\mu_k, \sigma_k^2 + \zeta_{gk}^2)$ and linear in ω, then, following Liaukonyte, Streletskaya, and Kaiser (2015), we have the following distribution for our WTP:

$$WTP \sim N\left(\mu_k - \frac{\lambda\sigma_k^2\zeta_{gk}^2}{2(\sigma_k^2+\zeta_{gk}^2)}, \frac{\sigma_k^4}{\zeta_{gk}^2+\sigma_k^2}\right) \tag{3}$$

which provide us with the following first order conditions for ζ_{gk}^2:

$$\frac{\partial\overline{WTP}}{\partial\zeta_{gk}^2} = -\frac{\zeta_{gk}\lambda\sigma_k^4}{\zeta_{gk}^2+\sigma_k^2} \tag{4}$$

$$\frac{\partial var(WTP)}{\partial\zeta_{gk}^2} = -\frac{2\zeta_{gk}\sigma_k^4}{\zeta_{gk}^2+\sigma_k^2} \tag{5}$$

The FOCs are both negative, indicating that both mean and variance of the WTP distribution fall with increases in ζ^2, the variance of the information signal. Recall that we assume that ζ^2 is a function of the variance of the agronomic efficiency of input k for those who attend the FFD, and thus $\zeta_{Ak}^2 > \zeta_{Nk}^2$. A wider array of information signals received by those who attend a FFD may decrease the attractiveness of the input (increases knowledge of both benefits and risks), and can potentially decrease mean WTP. On the other hand, a more complete picture of the range of benefits of the input can increase the precision of the WTP estimates and thus lower the variance of WTP. How do changes in ζ^2 affect the CDF of the WTP function for a particular agricultural input? As we describe below, changes in the mean of the WTP distribution will shift this curve, while changes in its variance will cause its rotation.

As shown in equation 2, farmers are willing to pay up to θ for a unit of the auctioned input, which is drawn from a distribution $F_s(\theta)$.[2] Parameter $s \in S$, a family of distributions, indicates the distribution's shape, with higher values indicating larger levels of dispersion. To translate this into market prices, we can analyze the inverse demand curve, $P_s(q) = F_s(1-p)$, where $q = 1 - F_s - 1(p)$ is the fraction of consumers that would purchase the agricultural

[2] We assume this distribution is twice differentiable on both s and Θ with support on an interval $(\underline{\theta}_s, \overline{\theta}_s)$.

input at a particular price p.[3] Figure 1 below provides an example relevant to our FFD context. Rotation of the demand curve from $F_s(\theta)$ to $F_s(\theta)'$ and a rightward shift of the CDF from $F_s(\theta)$ to $F_s(\theta)''$ can be caused through decreases in ζ^2.

In our empirical analysis, we attempt to identify whether FFD attendance has a differential impact on the distribution of WTP compared to non-attendance. As part of the experimental auctions in this study, enumerators read short descriptions of the products to all participants, which described potential benefits to crop yields of their use. Those who attend farmer field days, however, received more complex information signals that described risks and benefits of the inputs for different soil types and nutrient levels. If we assume that both μ_k and σ_k^2 are constant, but that $\zeta_{Ak}^2 > \zeta_{Nk}^2$ (the variance of the information signals is greater for FFD attendees), then our model has the following predictions:

$$\text{Prediction 1}: \quad \overline{WTP}_A < \overline{WTP}_N$$

which shows that we expect that the mean WTP among FFD attendees will be less than the mean WTP among FFD non-attendees. This follows from equations 3 and 4, and our belief that $\zeta_A^2 > \zeta_N^2$. The greater the variance in the information signals, the lower the WTP will be. Graphically, this would be evidenced by a CDF curve of WTP_A to the left of WTP_N. Our second prediction concerns the relative variance of the two groups:

$$\text{Prediction 2}: \quad var(WTP_A) < var(WTP_N)$$

that is, we predict the variance of the WTP values for FFD attendees to be less than for non-attendees. This follows from equations 3 and 5 and our same belief about ζ^2 among the two groups as above, which would be evidenced in more precise estimates of WTP among FFD attendees resulting from farmers better able to identify the value of the input compared to non-attendees.

[3] For full derivations, see Johnson and Myatt (2006) and Liaukonyte, Streletskaya, and Kaiser (2015).

Background and Data

The food security and income of farmers living across sub humid mid-altitude highlands in the west of Kenya depends for a large part on production of maize and common bean. Yields of these two crops however have stagnated or decreased over the past decade (FAO, 2018) due to limitations caused by various abiotic and/or biotic factors. To respond to some of these challenges, USDA and Cornell University implemented the project "Improving Bean Yields by Reversing Soil Degradation and Reducing Soil borne Pathogens on Small-holder Farms in Western Kenya" from 2012 to 2016. In partnership with IITA, multi-locational field trials analyzed the effects of vermicompost[4] and biochar[5] agricultural inputs on the production of common bush bean in Kakamega, Bungoma, and Busia counties. Findings from this study indicate that the two organic inputs can significantly reduce plant parasite damage and enhance crop yields as compared to control trials on the same farm (Were et al., 2015).

As part of the project, 21 farmers across the three counties of Kenya engaged in participatory demonstration trials with the researchers, which involved learning how to prepare and use biochar and compost on their own farm plots. In 2016, these trained farmers planted common bush beans on eight demonstration plots on their own farm. These plots included a control plot (no inputs), a plot where only biochar was used, another with only vermicompost, one with an agricultural inoculant, one with NPK fertilizer, and the remaining plots with combinations of these inputs. Results from these farmer-managed plots are in table 1, and demonstrate that most plots using biochar and vermicompost performed better than the

[4]Vermicompost is the end-product of the breakdown of organic matter by an earthworm, also called worm castings. If applied to the soil at the optimal rate vermicompost will improve crop production because it contains substantial amounts of nutrients, has a large water holding capacity and enriches the soil with micro-organisms (Jack and Thies, 2006).

[5]Biochar results from the thermal decomposition of biomass in the absence of oxygen, generating a type of charcoal. It is produced from left-over plant material of field crops on-farm like maize cobs and stovers, rice husks and haulms, sugarcane bagasse, coconut shells, and others. If applied to soil at the optimal rate, biochar helps to improve crop production by increasing the uptake of fertilizers, manure and water (Lehmann and Joseph, 2009).

control plot on the same farm.[6] As expected, plots with NPK fertilizer generally performed better than plots with only biochar or vermicompost added (given the nutrient density of NPK fertilizer), though plots with biochar and NPK fertilizer were often especially effective.

In May of 2016, the trained host farmers held FFDs for local farmers, showcasing differences in crop yields between the control and treatment plots. These host farmers distributed IITA research results to FFD attendees, informing them about the impacts of input practices over varying agro-ecological conditions. Attendees also learned information regarding composting and about cookstoves that generate biochar, which provided insights into organic input generation.

In our study, we identified the 18 villages in which these 21 trained farmers resided and then collected village-level lists of all household heads in these villages from local chiefs and village elders. A subset of the household heads was randomly selected for participation in the surveys and experimental auctions, resulting in a total sample of 884 individuals in 548 households. The survey instrument included questions on demographics, assets/income, agricultural production, market activity, and organization membership and activity. As can be seen in our summary statistics in table 2, the majority of the individuals surveyed identify their primary occupation as farming, cultivating an average of about one acre of land. From respondents across all villages, 24 percent stated that they had attended a FFD organized through this project. IITA chose the individuals holding FFDs based on their prior participation in the organization's activities, but importantly for our empirical identification, they were not specifically chosen by village or location within village. This means that the FFD locations were as good as randomly located within a particular village. Average distance from all surveyed households to the nearest FFD location within the village was 0.53 kilometers.

Given the generally positive impacts of biochar and vermicompost on host farmer crop yields in our sample (see table 1), we seek to determine the value that farmers placed on

[6] We are missing data from field days in two villages where the farmer harvested the demonstration plots prior to the arrival of the researchers (contrary to instructions).

these organic inputs. More specifically, we are interested in whether those attending a FFDs have a significantly different WTP distribution for these organic inputs compared to non-attendees. As discussed in our theoretical framework, we expect that the more comprehensive (and variable) information that farmers received at a FFD will both decrease average WTP and decrease the dispersion of their estimates. To elicit our WTP estimates, we use an experimental auction methodology after Becker, DeGroot, and Marschak (1964) (BDM) to determine farmer willingness to pay (WTP) for several agricultural inputs. An advantage of the BDM auction is that it is incentive compatible (represents true WTP), as it penalizes individuals for making bids outside of their true preferences, thus accurately aligning preferences with WTP measurements (Shogren, 2005). Moreover, it can be implemented with each participant separately, ensuring that there is no bias from the presence of any other individuals.

During implementation, we first conducted practice auctions with each participant for small food products to ensure that the participants understood the auction methodology. Project staff then presented 1KG and 5KG packs of DAP (diammonium phosphate),[7] biochar, vermicompost, cow manure,[8] and combinations of these inputs to each participant in a random order (though with DAP fertilizer always first), and the participant bid on each one. After bidding for each of the agricultural inputs, the enumerator's tablet computer selected a random input and price. If the participant had bid at least that random price for that input, s/he paid that price and received the input, otherwise s/he kept the full cash endowment.[9]

Because of potential liquidity constraints, in this auction, farmers received a cash endow-

[7] We chose to auction DAP fertilizer as it is one of the most commonly used inorganic fertilizer in Kenya and sold in most rural town markets.

[8] Cow manure was presented in 5kg and 25kg packs as it is a lower-valued input.

[9] Murphy et al. (2019) contains additional details of this experimental auction methodology. In practice, this experimental auction had two auction rounds, but we only use bids from the first round for this analysis. The sample drops outliers in bids so as to be consistent with Murphy et al. (2019). Bids are dropped from the analysis when the change in those bids for an individual between auction rounds is in the top or bottom 1% of the sample. We then additionally drop bids that are greater than 1400 KSh, which is twice the amount of the primary auction cash endowment, as those bids are considered unrealistic.

ment from the enumerators totaling 70 KSh (0.69 USD at that time) for each of two practice auctions and 700 KSh (6.90 USD) at the beginning of primary auction for the agricultural inputs.[10] Participants who did not use all of their cash endowment of the practice auction could carry it over to be used in the primary auction. Because many of the participants may have been unfamiliar with these inputs, prior to making bids, the enumerators read a short description of the agricultural inputs to the participants (included in Appendix A.1), which focused on the composition of the inputs and potential benefits on crops that may occur from their use. All participants therefore had some basic knowledge of the inputs auctioned, though we hypothesize that farmers attending the FFD had a more comprehensive understanding than those who did not attend.

In table 3, we present WTP results elicited from the experimental auction methodology divided between those who state that they attended a FFD and FFD non-attendees. In general, we do not find significant differences in bids between the two groups in these raw results. However, we do see lower means for biochar and vermicompost quantities among FFD attendees compared to non-attendees, which follows our model's predictions and anticipates our later findings. Figures 2 and 3 show the respective cumulative density functions of bids for biochar (1KG) and the biochar (1 KG)-DAP (5 KG) WTP ratio divided between these two groups (figures for other inputs and ratios are shown in Appendix figures A.2.1-A.2.6). In each of these figures we see that the CDF of attendees is to the left of the CDF of attendees suggesting a notable impact of attendance/non-attendance at FFDs on farmer WTP.

To understand better the selection into attendance and non-attendance at the FFD, in table 4 we show some of our variables divided between attendees and non-attendees at the FFDs. Attendees at the FFD are more likely to have been farmers (as a primary occupation),

[10]Significant deliberation went into the decision regarding the size of the cash endowment. Providing too much could cause overstated WTP estimates (Loureiro, Umberger, and Hine, 2003). On the other hand, two little could lead to a censored upper bound, where farmers are unable to bid their true WTP given insufficient liquidity. We chose 700 KSh as it is roughly twice the value of the most expensive input auctioned, following other studies using experimental auctions in SSA (Morawetz, De Groóte, and Kimenju, 2011; De Groote et al., 2016).

have been in contact with a NGO, have larger farmers, have used compost, have used NPK, and are less likely to have used urea fertilizer. Most of these correlations are to be expected: those connected with an NGO are perhaps more likely to have heard about the FFD, and those already using compost may have been more interested to learn more about organic inputs. Also, those who have a primary occupation as farming would be more interested in learning about new agricultural inputs. Another key correlation is that attendees at a FFD live significantly closer to the FFD site, which as we show below, is a key to identifying our empirical model.

Empirical Method and Identification

Using the results from our experimental auctions that elicit WTP for organic inputs, we seek to determine the causal relationship between attendance at the farmer field days (FFDs) and the valuation of these inputs by the randomly selected participants. . However, establishing a causal relationship is complicated by the fact that attendance at a FFD is endogenous with WTP: there are numerous observed and unobserved variables that may influence attendance, such as an individual's experience, inherent motivation, or relationships with the FFD host or other attendees. As discussed earlier and shown on table 4, we find many significant differences between attendees and non-attendees, such as farm size and prior use of organic inputs.

To identify this relationship between field day attendance and organic input bid, we include distance from an individual's household to the nearest FFD location as an instrumental variable (IV). The vast majority of individuals in the sample (88%) have either inherited their land or married into it. Moreover, as long as the homestead locations were not chosen to be close to the FFD, we can assume that the homestead location is exogenous in our model. However, for the distance between the FFD site and homestead to be a valid instrument, we must show that the FFD location is also exogenous. In our case, we are fortunate in that IITA did not select the host-farmer based on any consideration of his/her location within the village. In fact, IITA did not even have data on the village of the host-farmer prior to this study. As a result, the distance between an individual's homestead and nearest FFD site is exogenous in our model and we rely on this exogeneity for our identification. Additional falsification tests for this instrument are located in the Robustness Checks section.

In figure 4, we show an example of homestead locations and the FFD site from a representative village in our sample, with colors coded based on whether the members of the household attended the field day. This figure suggests that there is a negative correlation between distance from FFD site and homestead location. We confirm this strong correlation in our first stage estimation results (table 5), which show that a one kilometer increase in the distance from a homestead to the FFD location corresponds to about a 39 percentage point decrease in the likelihood of attending the FFD (controlling for household/demographic characteristics and using village fixed effects). We therefore believe our instrument is both strong and valid and can be used to identify our empirical model.

We thus conduct the following two-stage least square (2SLS) estimations, with equation 6 measuring the impact of field day attendance on organic input bids, and equation 7 analyzing the effect of field day attendance on the WTP ratio of organic bids to DAP (5 KG) bids.

$$Bid_{ik} = \alpha + \beta_1 \gamma_i + \beta_2 M_i + \beta_3 DAP_i + \sum_n \beta_n X_{ni} + I_k + \vartheta + \varepsilon_{ik} \tag{6}$$

$$\phi_{ik} = \alpha + \beta_1 \gamma_i + \beta_2 M_i + \sum_n \beta_n X_{ni} + I_k + \vartheta + \varepsilon_{ik} \tag{7}$$

where $\phi_{ik} = Bid_{ik}/DAP_i$, Bid_{ik} is the bid by individual i for organic input k, DAP_i is individual i's bid for a 5 KG sack of DAP fertilizer,[11] and γ is an instrumented, binary variable (described above) indicating whether the individual stated that s/he attended a FFD related to organic inputs. Variable M is the quantity of cash endowment that the

[11] Five individuals bid zero for DAP (1 KG) and DAP (5 KG) and are therefore dropped from this estimation. We include a robustness check with an alternative WTP ratio (using the average DAP bid rather than the bid for 5 KG), with results in table A.7. In this model, we include bids for 1KG and 5KG of biochar and vermicompost.

participant had at the time of the auction.[12] Variable I_k are input-level controls, and ϑ are village, enumerator, and survey month fixed effects.

An individual's bid for DAP fertilizer is included in both equations 6 and 7 – as a control variable in the former and as part of the dependent variable in the latter. Why do we do this? Because DAP was always presented first to the respondent (prior to the organic inputs), individuals likely use their bid for DAP as a benchmark for future bids for the organic inputs (see Morawetz, De Groóte, and Kimenju (2011) for a similar situation involving maize bids in Kenya). Moreover, research shows that bidding for unfamiliar goods is influenced by known prices of outside, familiar options (Cherry et al., 2004; Bernard and He, 2010). Indeed, we find a strong correlation between an individual's WTP for organic input and that individual's WTP for DAP.[13] Either scaling the organic input bids by this variable to create a ratio or including the variable in our estimation controls for this potential benchmarking effect.

The bid for DAP, however, is likely an endogenous variable in our empirical model. For this reason, in equation 6, we employ a second instrument in addition to the distance between homestead in FFD location. Using an IV strategy employed by Hausman, Leonard, and Zona (1994) and Murphy, Berazneva, and Lee (2018) (among others), we use the except-own average of bids for the DAP input in each village. As table 6 shows, this instrument is highly correlated with an individual's own bid for 5 KG of DAP. This instrument is also valid, assuming that random individual-level factors that influence one's own DAP bid are independent of other individual's bids. Because we conducted these auctions with each respondent alone and separated from others (including his/her spouse), we believe that this assumption is plausible.

Additional specifications of estimations 6 and 7 also include measures of soil nutrient levels. Individuals were asked their perception of their soil health (on a scale of 1 to 5),

[12] Recall that individuals received a cash endowment for practice auctions in addition to a cash endowment at the beginning of the input auction. The results of the practice auction often led to the spending of some of the practice auction endowment funds, which led to differing amounts of money held by individuals at the beginning of the main auction round.

[13] Specific estimation results for the correlation between WTP for organic inputs and DAP are available on request.

and we also measured their exact soil nutrient levels.[14] A number of other specifications include additional variables, such as whether the individual was a FFD host, whether s/he was connected with an agricultural NGO, and whether s/he received any information from government ministries.

Our identification of a causal relationship of attendance at a FFD in May, 2016 and WTP that was measured between July and November, 2016 also rests on a stable unit treatment value assumption – that there was no spillover effect between those who attended and did not attend a field day. In other words, that those who attended a FFD did not influence those who did not attend with respect to the auctioned agricultural inputs. As we discuss in greater detail in the robustness checks, we found that there was little secondary information diffusion – that those who attended a FFD did not tend to share this information with others in the community. However, to control for this possibility and for additional analysis, in our robustness checks we also show estimation results using knowledge of the agricultural inputs rather than attendance at a field day as the primary variable of analysis. As we later discuss, this substitution augments the magnitude of our results.

We now turn to our models second prediction and analyze the impact of FFD attendance on WTP dispersion. We do this using the following mixed models, incorporating both fixed and random effects:

$$Bid_{ik} = \alpha + \beta_1 u_{ik}\gamma_i + \beta_2 M_i + \beta_3 DAP_i + \sum_n \beta_n X_{ni} + I_k + \vartheta + \varepsilon_{ik} \tag{8}$$

$$\phi_{ik} = \alpha + \beta_1 u_{ik}\gamma_i + \beta_2 M_i + \sum_n \beta_n X_{ni} + I_k + \vartheta + \varepsilon_{ik} \tag{9}$$

where u measures the input-level impact of field day attendance on organic input bids. To test for differences in the level of dispersion in the WTP function between attendees and

[14] We measured levels of nitrate, phosphate, potassium, sulphur, and active carbon present in the soil using SoilDoc, which adapts standard wet chemistry analysis of soil samples into a low-cost and portable kit. See Murphy et al. (2019) for additional information.

non-attendees, we divide u into fixed and random coefficient estimates:

$$u_{ik} = \bar{u}_k + \tau_k \psi_{ik} \tag{10}$$

The fixed component, $\bar{u}$, estimates the effect of the field day attendance on the mean of the WTP distribution, while τ measures the effect of attendance on the level of dispersion of the distribution. The unobserved random variability between individuals, ψ_{ik}, captures the heterogeneous impacts on WTP within both groups (Berry, 1994).[15] By combining equation 10 into equations 8 and 9, we can estimate a model to analyze the effect of FFD attendance on the dispersion of the WTP distribution.

Results

Results from our 2SLS estimations (equations 6 and 7) with standard errors clustered at the village level[16] indicate that attendance at farmer field days (FFDs) had a large and statistically significant impact on Bid_{ik} (the participants' bids for organic inputs) and ϕ_{ik} (the WTP ratio of organic inputs to DAP). In-line with the predictions from our model, attendance at a FFD decreased an individual's WTP for organic inputs (WTP ratio for organic inputs relative to their WTP for DAP). Tables 7 and 8 contain our primary results.

In table 7, we see that across all specifications, attendance at a FFD decreased organic input bids by about 30 KSh (significant in most specifications at the p=0.05 level). Our preferred specification is in Column 4, which controls for demographic and household characteristics as well as the farmers' lab-tested soil nutrient levels, shows a negative impact on mean WTP for the organic inputs of 29.50 KSh, which approximates to sixteen percent of

[15] Variable ψ_{ik} is distributed $N(0, D)$, where we assume all covariances in D are zero. This is primarily due to computational limitations, but since the auctions were held independently from one another, we would assume that independent variances in this context are likely to exist.

[16] There may be some concern given the relatively small number of clusters using villages (18). To mitigate these concerns, we conduct Wild Bootstrap estimations after Cameron, Gelbach, and Miller (2008), which corrects for the small number of clusters. P-values from the original estimations in table 7 are shown together with p-values from the bootstrapped estimations in Table A.5. We can see that in all six of the specifications, the wild bootstrapped p-values are similar than those in our original estimations, indicating that the relatively small number of clusters are not biasing our standard errors downward.

the average WTP value across all organic inputs. Also as expected, average bid for DAP fertilizer is highly statistically significant with the bids for organic inputs, as farmers are likely using their bid for DAP fertilizer as a benchmark for their bids for the less familiar organic inputs. Columns 5 and 6 report results of specifications that include variables indicating whether the farmer was a "Project farmer" (FFD host), whether the farmer received information from the agricultural ministry through extension projects, and whether the farmer had contact with an agricultural NGO. With the exception of the NGO contact, which had a negative impact on bids, the other variables do not show any impact. Finally, we see that across specifications, higher levels of active carbon measured in a farmers' soil had negative impacts on bids for organic inputs. This result is likely due to a belief among farmers with higher quality soils that the application of organic inputs is less necessary.

We report the results using the WTP ratio of organic inputs to DAP (ϕ) in table 8. These estimations show attendance at a FFD decreased ϕ by between 0.12 and 0.15. Estimation 4, our preferred specification that controls for demographic and household characteristics as well as the farmers' lab-tested soil nutrient levels, shows that attendance at a FFD decreases ϕ by 0.123. In other words, attendance at a FFD decreases an individual's WTP for an organic input relative to WTP for DAP by an average of 12.3 percentage points, significant at the p=0.05 level. Inclusion of the lab-tested soil nutrient levels in Columns 4-6 show that greater amounts of nitrogen present in the soil have a statistically significant and positive impact on the relative WTP for organic inputs to DAP. This is expected as we believe that farmers who have more nitrogen their soils are less willing to pay for additional DAP (a commercial nitrogen input) relative to organic inputs. Unlike in the results for organic input bids, we do not find that participation in an agricultural NGO significantly affects the WTP ratio (Column 6 in table 8).

We also analyze this impact by calculating the marginal effects of attendance at a farmer field day on bids for the auctioned inputs (figures 5 and 6). We specifically look at biochar, as we have crop yield data from field trials using this input in the same region (discussed below in the extensions and robustness checks). Using our preferred specification from table 8, we find that individuals who did not attend the field day have a WTP ratio of 1KG (5KG) biochar to 5KG DAP of 0.23 (0.82) respectively, setting all other variables at their mean (95% confidence interval of 0.21 and 0.25 (0.79 and 0.85)). On the other hand, those who did attend a FFD had a WTP ratio of 1KG (5KG) biochar to 5KG DAP of 0.12 (0.71), again after setting all other variables at their mean (95% confidence interval of 0.05 and 0.19 (0.65 and 0.78)). Post-estimation pairwise comparisons of these marginal estimates demonstrate a statistically significant difference (at p=0.01). Given this result, we can conclude that attendance at a FFD has a significant and strongly negative impact on farmer valuation of biochar relative to DAP. The same analysis performed for the organic input bid alone (not the ratio) shows similar results.

From our analysis thus far, it seems clear that Prediction 1 from our model, that $WTP_A < WTP_N$ (the average WTP among FFD attendees is less than the average WTP among non-attendees) is valid. As described earlier, this is likely due to a higher variance in the information signal regarding input k to attendees at a FFD than to non-attendees. In other words, FFDs teach farmers about the varying profitability of input k that depends on soil nutrient levels, which can decrease its universal attractiveness. On the other hand, more varied information provided to farmers that teaches farmers about the risks and benefits of the input for different soil conditions and environments can enable better estimates of the WTP, increasing the precision of WTP estimates. To determine whether this is the case, we next analyze our data using our mixed model incorporating random effects (equations 8 and 9).

Table 9 shows results from these mixed-model estimations, and we focus our analysis on the standard deviations of the random coefficient estimates.[17] By not including a constant for the random effects, we are able to directly compare the standard deviations of the WTP

[17] "Attended Field Day" and "DAP (5kg) bid" variables in these estimations are predicted using our first stage estimation results, and standard errors are corrected using bootstrapping. While the fixed effects portion of these estimations is not the focus of our analysis (preferring the 2SLS results described earlier), they show impacts that are generally similar using our 2SLS estimations.

functions between attendees and non-attendees. The results show the variation in the impact of the FFD attendance among individuals on their WTP, hence providing us with an estimate of the effect on the dispersion of bids by an input. Column 1 and 2 correspond to above equations 8 and 9 respectively. The results of both show that the standard deviations of WTP (WTP ratio) for attendees is significantly less than for non-attendees, indicating more precise estimates. These results thus provide supporting evidence to validate our model's second prediction that $var(WTP_{Ak}) < var(WTP_{Nk})$.

Results from our 2SLS and mixed-model estimations show significant impacts from attendance at FFDs on the distribution of respondents' WTP for the agricultural inputs. The evidence suggests that information signals received by FFD attendees had greater variance (due to various levels of success of the demonstration plots, more knowledge about risks and benefits, etc), lowering mean WTP. Recall that the only information that non-attendees may have had regarding these inputs was the few sentences read to them by project staff at the time of the auction. This was likely insufficient information to enable matching between personal preferences and farm characteristics with the inputs. We find supporting evidence that FFD attendees had more precise WTP estimates, resulting in a rotation of the WTP CDF. We explore additional results and extensions to our analysis in the following section.

Extensions and Robustness Checks

There are several additional aspects that can be considered with regard to our estimation, which we discuss below.

Knowledge of input rather than attendance at field day

There are some concerns with using stated attendance at a FFD to measure the impact of field day information on farmer WTP for the organic inputs. Farmers could report attending a FFD, but may never have actually attended. On the other hand, farmers could have attended, but not paid attention to any of the information discussed. It is also possible that farmers heard about inputs such as biochar from others in their network outside of attendance at a FFD itself. As a robustness check, we conduct additional estimations that use measures of *knowledge* of the agricultural inputs rather than attendance at a FFD. In addition to asking the farmer during the survey whether s/he attended a FFD, we also asked the farmer whether s/he had heard of biochar prior to the visit by the enumerators. If the farmer had heard of biochar, the enumerator asked the respondent to describe it and indicated in the survey whether the farmer had actual knowledge of the input. As key independent variables in separate estimations, we thus use 1) whether the farmer had heard of biochar prior to the survey, and 2) whether the farmer can describe biochar. In our random sample, 24% of the 884 individuals report attending a FFD, 19% of the sample had heard of biochar, and only 13% could describe biochar. There were relatively few individuals who had knowledge of biochar but did not attend a FFD: of the 668 farmers who did not attend a FFD, only 24 had heard of biochar, and only 8 could accurately describe biochar. This suggests that information presented at FFD had not necessarily spread rapidly to those who did not attend the FFD.

Using these alternative independent variables, we conduct separate 2SLS estimations of "heard of biochar" and "can describe biochar" on organic input WTP and relative WTP for organic inputs compared to DAP using our preferred specifications from the previous section (controlling for soil nutrient levels, household and demographic characteristics, village, survey month, and enumerator). Like field day attendance, these "knowledge variables" are endogenous in our model given the numerous omitted variables that are likely correlated with both knowledge of biochar and WTP for the inputs. We therefore use the same identification strategy as earlier, given that knowledge of biochar is highly correlated with distance to the FFD site. Indeed, first stage estimations in table A.6 show a strong negative correlation between distance from field day site and each of the knowledge variables ("heard of biochar" and "can describe biochar").

The results of these new estimations, shown in table 10, indicate that using the knowledge variables rather than the attendance variable increases the magnitude of the effects on both WTP and the WTP ratio for the inputs. Columns 1 and 5 in table 10 repeat the results from our preferred specifications in tables 7 and 8 using field day attendance as the instrumented variables. Columns 2 and 6 present the same specification, but using "heard of biochar" (instead of attended field day) as the instrumented variable, and in Columns 3 and 7 we use "can describe biochar" as the instrumented variable. We can see that as we move from Column 1 to Column 3, the coefficient magnitude of the primary independent variable in the estimation increases from -29.5 to -36.2 to -40.7 for "attended field day," "heard of biochar," and "can describe biochar" respectively. The impact on the WTP ratio likewise increases in magnitude as we move from Column 5 to Column 7. These results indicate that the attendance at a FFD variable, which includes any farmer who states that they were at a FFD, likely underestimates the impact of a FFD, as it may include individuals who falsely claim they were there or who went but did not pay attention. The latter two estimations may also be picking up effects from information diffusion, as some individuals who did not attend the FFD state that they had heard of biochar or had knowledge of biochar. Given the greater magnitude of our results using knowledge-based measures, it appears that the attendance variable used in our primary results provides a conservative estimate of the program impact on respondents.

Demonstration Plot Results and WTP

Another question we investigate is whether farmer WTP for organic inputs are correlated with the success of the demonstration plots at a particular site. If field day attendees see crop yields that are significantly better on plots where organic inputs are applied, there may be a differential impact on WTP compared to attendees who see a field day where the plots with the organic inputs are performing less well. As table 1 shows, demonstration plots of organic inputs on four of the nineteen sites in which we have data performed less well than the control plot, which perhaps could have decreased WTP. An optimal strategy to explore this question would be to add an additional variable to our estimations indicating whether the organic input demonstration plots on a particular site had better yields than the control. Interacting this variable with "attended field day" would then indicate the impact of these differential site-level plot results on farmer WTP.

Exploring this question is challenging for several reasons. First, we are missing data from two of eighteen villages. In these, the host farmers harvested their plots prior to the arrival of the researchers, so measurements were not taken of the demonstration plots. Second, all villages (except one) have one field day site. The lack of within-village variation for most of the villages combined with the use of village fixed effects means that the entirety of the impact we would observe in our results would come from a single village (Village 5), which had several field day site. Third, the interaction of attended field day and an indicator variable for the success of the organic demonstration plots would require an additional instrument. In situations like this (an endogenous variable interacted with an exogenous variable), the literature suggests interacting an instrument with the exogenous variable. In our case, when we do this, we have very weak instruments (results available on request). We therefore conclude that this is an interesting question for analysis in future studies that have greater within-cluster variation in field day results.

Falsification Tests for Instrument

Earlier, we explained that the validity of our IV (distance from homestead to field day) is likely exogenous in our empirical model due to the effectively random location of the field day within each village. However, we conduct additional tests on our IV strategy to provide additional assurance of its validity.

As an initial falsification test, we first seek to determine whether it is not the distance to the FFD site that matters, but distance to a particular individual's homestead in the village. We test this by running simulations with randomly sampled homesteads in the village serving as a "fake" FFD site. For each simulation, we test whether the randomly chosen homestead in each of the villages provide us with a significant first stage (distance between "fake" FFD site and FFD attendance). If we find a large percentage of these simulated distances provide us with significant results, this would suggest that it was distance to other homesteads that was driving the correlation of our distance IV with field day attendance. If this was the case, we would need to develop alternative explanations to defend the exclusion assumption of our IV, which could threaten our identification strategy.

In each of the 10,000 simulations, a randomly chosen homestead in each village was designated as the "fake" FFD location. Using the distance between each homestead and the "fake" FFD location, each simulation conducted a first stage estimation (specifically that of Column 3 in table 5), calculated F-statistics, and p-values for the distance to the fake FFD variable. The results located in table A.8 show that only a small share of these estimations had statistically significant results. Only five percent of simulations resulted in an F-statistics above 6.26 or a P-value less than 0.02. This is compared to a F-statistics of 26.57 and p-value of 0.00 in our first-stage estimation using distance to the actual FFD. These simulated results demonstrate that distances to random homesteads that serve as fake field day locations are generally not strongly correlated with field day attendance and our IV genuinely represents a strong correlation between distance to and attendance at the field day.

In another test, we analyze the potential impact of outlying homesteads in our estimations. While we described that field day locations were effectively randomly located within each village (as IITA did not choose location based on village boundaries), there may still be concern that the instrument is being driven by those located far from the village center. The argument may be that those located far from the village center are less likely to attend a FFD. It may also be that those farmers located far from the village center have fundamental differences in their relative WTP for the inputs, which if true would violate the identification assumptions. We test this by re-estimating our first-stage with distance between homestead and village center as our potential instrumental variable. Our results, located in Table A.9, are reassuring. There is very weak correlation between distance from village center and field day attendance. Moreover, unlike the strong negative correlation we found between distance from the field day site and FFD attendance, the correlation here is weakly positive. We conclude then that outlying homesteads in the sampled villages are likely not a threat to the validity of this instrument.

Family Connections with FFD host

Another interesting avenue of exploration is whether a farmer has family connections with the FFD host, and if so, what are the potential ramifications. We have data on whether an individual states that s/he is immediate or extended family with the FFD host farmer. We can use this information in two ways: as a control variable in the primary estimation or as an additional instrumental variable. The intuition for an IV is as follows: if there exists a family connection with the FFD host, an individual is more likely to attend the FFD. However, blood ties with an individual are not a choice variable, which suggests it may satisfy the exclusion restriction.

We first simply add a binary variable as a control to our estimation, which indicates whether an individual is part of the FFD host's extended family. This is the case for 36% of the sample, as shown in the summary statistics (table 2). We show the estimation results with this additional control variable in Columns 4 and 8 of table 10, which indicate no significant correlation between this variable and either WTP for organic inputs or the ratio of organic input to DAP WTP. Additionally, we find little impact of the inclusion of this control variable on the "attended field day" coefficient in either case, which increases in magnitude only slightly.

We also test the suitability of this variable as an additional IV. In Table A.10, we show re-estimations of the first stage including both distance from homestead to the FFD site and family relation to the FFD host farmer as potential instruments. Clearly visible from these estimations is the lack of strong correlation between family relationship and attendance at the FFD when we also include distance. Therefore, we are not able to use this family relationship variable as an additional IV for our identification.

Monte Carlo Simulations for the Value of Biochar

Here, we seek to compare participants' WTP for inputs to their actual value. Organic inputs, however, do not necessarily have a market price. Because of high transportation costs, organic inputs are often produced on-farm in rural SSA (Place et al., 2003). Therefore, estimating the value of organic inputs can be approximated by the value of the increase in crop yield per hectare from a one-unit increase in the input per hectare. For our analysis, we focus on the value of biochar, as it is an input that was taught at the FFDs and recent research provides us with parameters to use to estimate the value of the input. We establish this average value of biochar using Monte Carlo simulations with parameters informed by an experiment carried out by Roobroeck et al. (2019), which analyzed data from three agro-ecosystems in Kenya over multiple growing seasons.

Findings from that experiment show that applying 1 ton of biochar (dry weight – DW) ha^{-1} increased grain productivity by 0.34 to 1.24 ton ha^{-1} compared to a no input control over the three years for all study areas (table A.3). Adding 1 ton of DW biochar ha^{-1} to maize that was receiving DAP fertilizer raised the maize yields by an additional 0.17 to 0.63 ton ha^{-1} over the same time period.[18] The persistence of these yield impacts three years later after a one-time application of biochar at 1 ton ha^{-1} show that biochar is particularly useful under resource-limited conditions in smallholder farming systems.

Using these results (table A.3), we parameterize a Monte Carlo simulation to estimate the value of biochar in western Kenya. In table A.4, we show the results of these simulations for the distribution of the parameters and the final two-year present value of biochar. We assume a discount rate that ranges between 0 and 0.1, and also assume that farmers who

[18] Higher yield responses were achieved when applying biochar at rates of 5 and 10 ton DW ha^{-1}, ranging from 1.05 to 3.17 ton ha-1 compared to plots where no inputs were applied, and 0.66 to 1.84 ton ha-1 compared to when exclusively inorganic fertilizers were applied.

attended a FFD are aware that biochar will provide two years (four seasons) of benefits from a single application. Using results described above from Roobroeck et al. (2019), the parameter values in our simulation of biochar's impact on maize yields range from 0 (i.e. a 1 ton/ha application of biochar has no impact on maize yield) to 1 (i.e. a 1 ton/ha application of biochar increases maize yields by 1 ton/ha). With 10,000 simulations, and using a distribution for the price of maize centered on the village maize price at the time of our survey, the results of our simulation show a mean per-kilo two-year present value of biochar to be about 45 KSh (table A.4). We subsequently compare this estimate to WTP findings for organic inputs between attendees and non-attendees at FFD in our results. Marginal calculations (at means) of our 2SLS calculation of field day attendance shows average biochar (1 KG) WTP of 49.2 KSh among those attending a FFD and 72.3 KSh among non-attendees. We therefore find that the average bids among FFD attendees are closer to the calculated biochar value than average bids of non-attendees.

Discussion

Farmer field days (FFDs) are a potentially effective method to diffuse productivity-enhancing information or technology within developing country communities. Often used to multiply the impacts of intensive, participatory, on-farm programs such as a farmer field schools (FFS), which are costly to implement, FFDs are one day programs hosted by a trained farmer and attended by his/her peers in the farmer's village. However, to this point, there has been few economic evaluations to measure the impacts from these FFDs. This is in part due to identification problems: attendance at a FFD is a choice by the farmer, which is influenced by numerous unobserved factors such as motivation and connections with the FFD host. As a result, there is little evidence whether FFDs are effective in teaching smallholder farmers tools to improve their productivity.

We model FFD attendees and non-attendees as receiving different information signals with different variances, where attendees receive a greater variety of information informing of the benefits and risks of the input and varying profitability depending on soil characteristics of an individual's farm. Farmers who attended FFDs also saw the effects of the inputs on farmer plots – most field day sites with organic input demonstration plots showed an improvement in crop yields compared to control plots, although often the yields were less than other demonstration plots only using NPK fertilizer. Most non-attending farmers, on the other hand, heard about these organic inputs only from a brief description given by enumerators prior to the experimental auctions. The information at the FFDs potentially both shift and rotate the willingness to pay (WTP) CDF - potentially decreasing WTP through an increased knowledge of both risks, benefits, and the variability of profits, but broader knowledge also increasing the precision of the WTP estimates by farmers. To test our model and examine whether these shifts and rotations took place, we randomly sampled individuals from villages in western Kenya that held FFDs to disseminate information about novel organic inputs in 2016. We implemented Becker-DeGroot-Marschak experimental auctions with the entire random sample for several organic inputs and DAP fertilizer, a common inorganic fertilizer in the area. To identify the causal impact of attendance at a FFD on WTP for the organic inputs, we used GPS-measured distance between an individual's homestead and the nearest FFD location (the host farmer's farm), which was effectively randomly determined within each village.

Using 2SLS with village-level fixed effects, we find that attendance at a FFD decreases both the farmer's WTP for the featured organic inputs and the WTP ratio of organic inputs to DAP compared to farmers that did not attend a FFD. As a robustness check, substituting a knowledge variable for the attendance at the FFD variable increases the magnitude of the impact on WTP for the inputs. We also use a hierarchical, mixed model with random and fixed effects to analyze differences in variation between the WTP distributions of attendees and non-attendees. As our model predicts, we find more precise estimates among those who attend a FFD. These results speak to the potential for FFD to transmit real information that enables matching between a farmer's needs and the agricultural product.

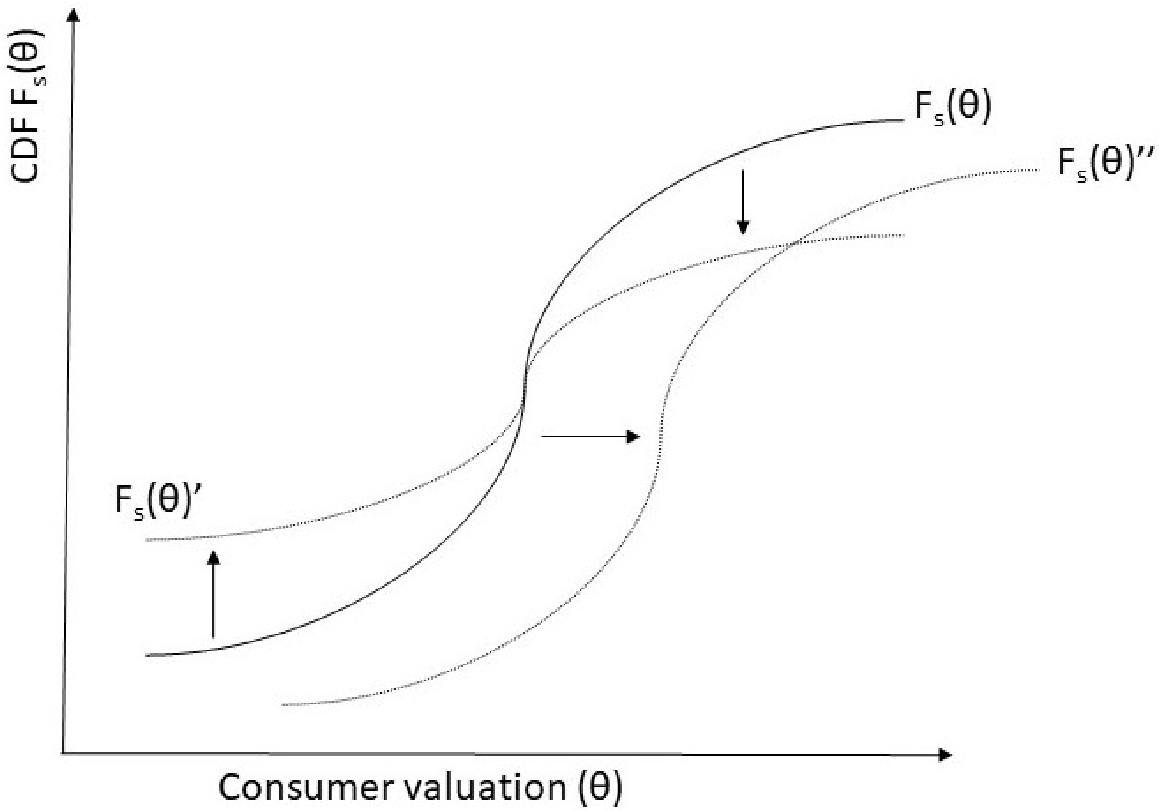
We include numerous other robustness checks including falsification tests of our instrumental variable (distance from homesteads to the FFD site). We find that randomly located field day sites in the village are generally uncorrelated with field day attendance, strengthening our argument that it is the distance to the field day site, not to other individuals' homesteads in general that drive our identification. Moreover, we show that outlying homesteads are not less likely to attend the FFD by using a variable composed of the distance of a homestead to the village center as an alternative (and ineffective) instrument. We also show that family relationships between farmers and the FFD host farmer do not drive our results by including this variable in the second stage as a control variable, and by showing that it is ineffective as a potential second instrument. As an extension, using field day from a separate project using biochar in western Kenya, we conduct a Monte Carlo simulation to estimate an actual value of biochar. Doing this, and comparing the results to marginal estimates of average WTP of biochar by FFD attendance, we find that the average WTP for FFD attendees was significantly closer to our estimated value of biochar compared to non-attendees.

This study demonstrates that FFDs can be effective at transmitting information to individuals in a developing country context. While FFDs are typically one day events and cannot necessarily transfer complex technology or practices to those in attendance, they can be a useful tool for cost effective diffusion of more simple or straightforward productivity-enhancing techniques (Ricker-Gilbert et al., 2008). As there continues to be a debate in the literature as to the efficacy of farmer field schools (FFS) (Van den Berg and Jiggins, 2007; Feder, Murgai, and Quizon, 2008; Davis et al., 2012; Waddington et al., 2014), this research shows that FFDs can be added to FFS programs to increase their reach and cost effectiveness.

While we find significant impacts of this FFD in western Kenya, we cannot claim that the specific results found here can be expected in other FFDs in other contexts (geography, information intervention, etc). These results are for a specific product, location, and time.

Nonetheless, we believe that the results are indicative of the potential of FFDs to shape perceptions of attendees and magnify impacts of other programs, which otherwise may not be cost effective.

Because of the highly degraded soils in much of Sub-Saharan Africa, crop yields are often below potential resulting in food insecurity for many small-scale farmers. Therefore, rigorous evaluations of methods for disseminating information on productivity-enhancing technology are needed. This study demonstrates that one method of information diffusion, farmer field days, can result in real learning from those in attendance, and as a result should be considered as a cost-effective method for information diffusion in future development projects.



Note: Figure represents potential shifts and rotations of consumer CDFs due to new information. A clockwise rotation of the CDF, potentially due to increased detailed knowledge among a sample about a particular product, is illustrated as a change for the function from $F_S(\Theta)$ to $F_S(\Theta)'$. A shift in the CDF, on the other hand, due to perhaps promotional information about a product, is illustrated as a shift from $F_S(\Theta)$ to $F_S(\Theta)''$.

Figure 1: Rotations and Shifts of Farmer CDF

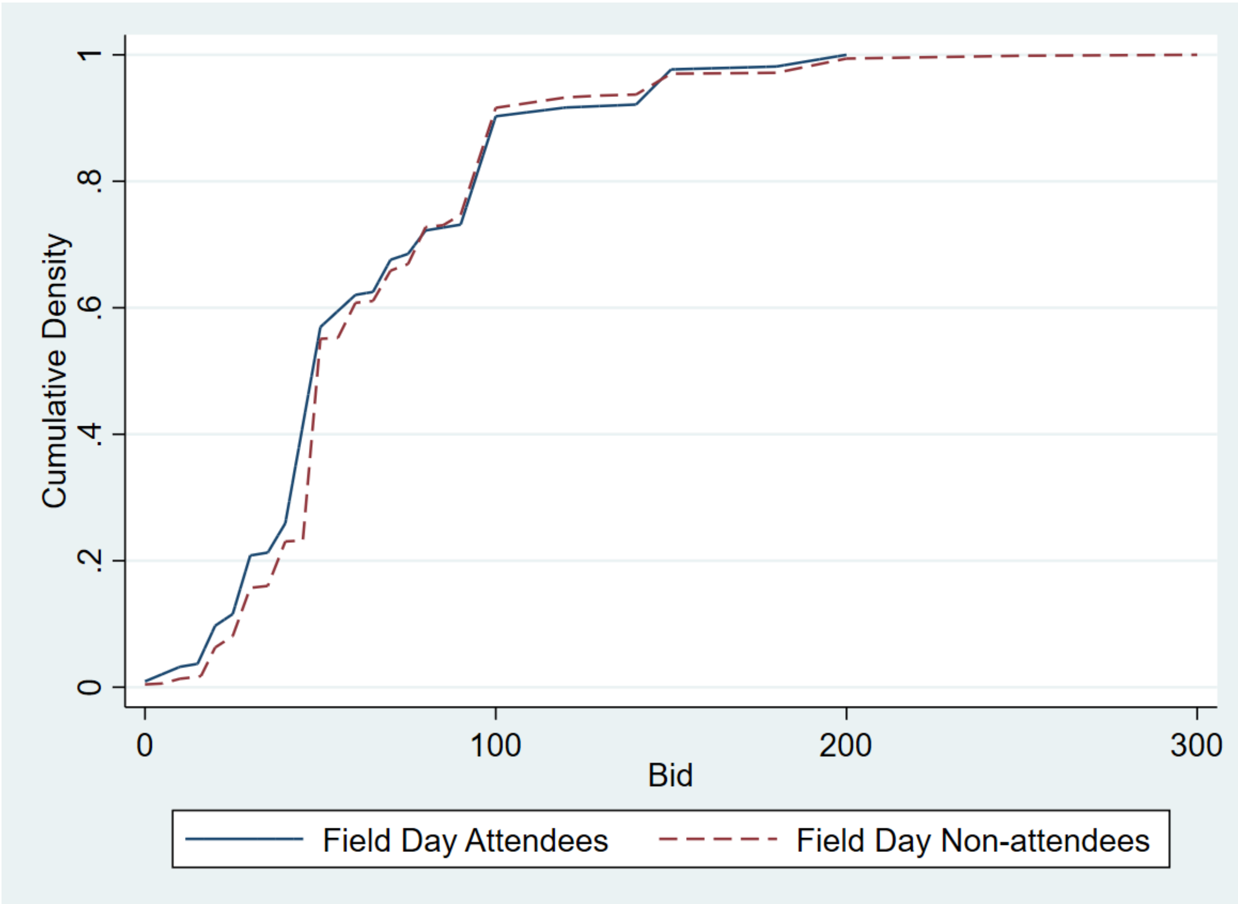


Figure 2: Cumulative Distribution: Biochar (1KG) WTP

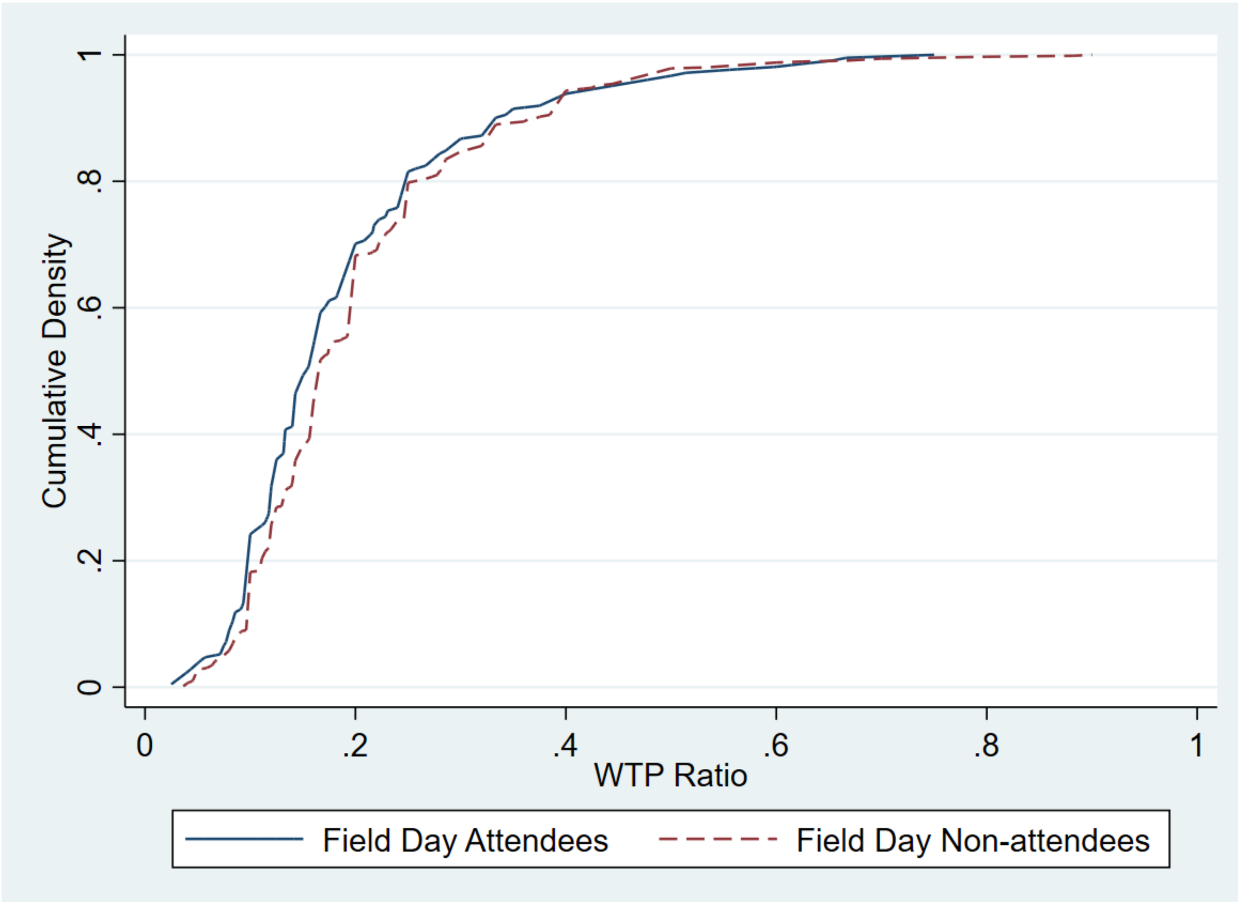
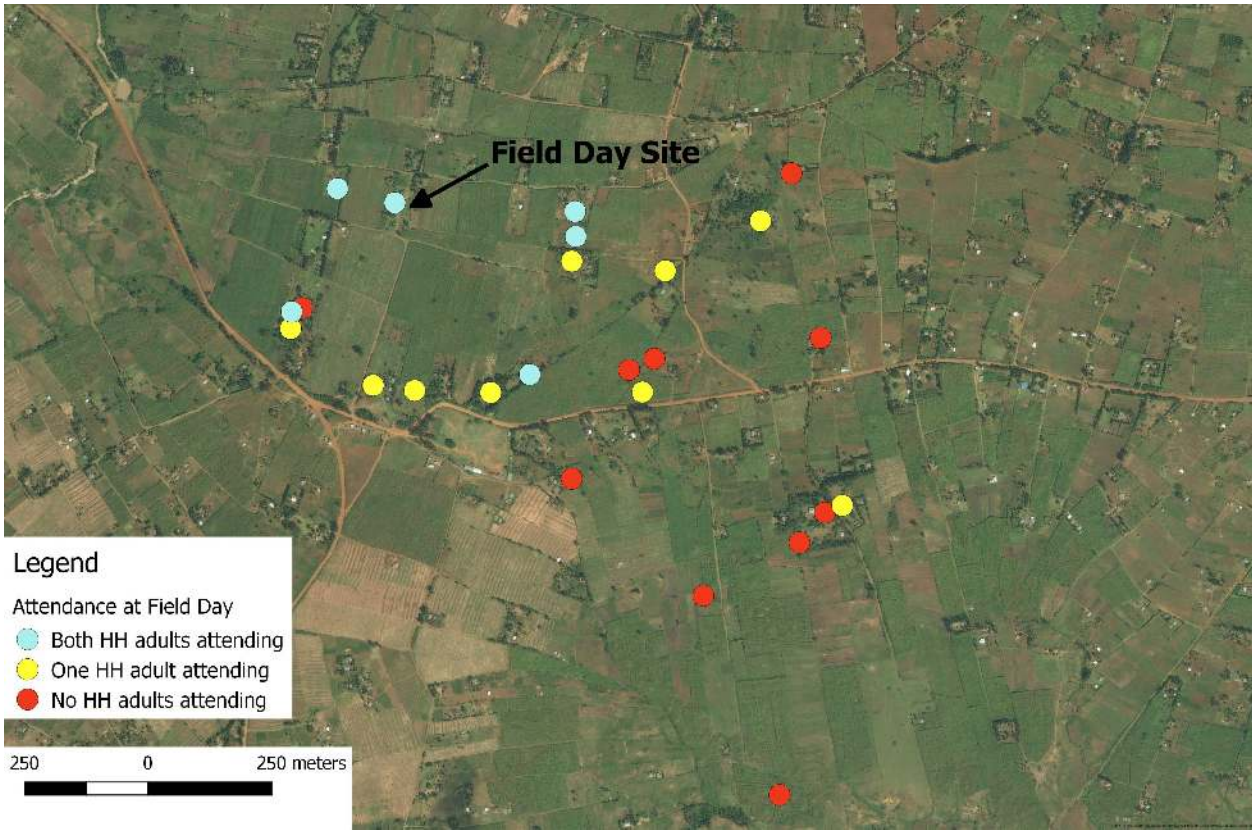
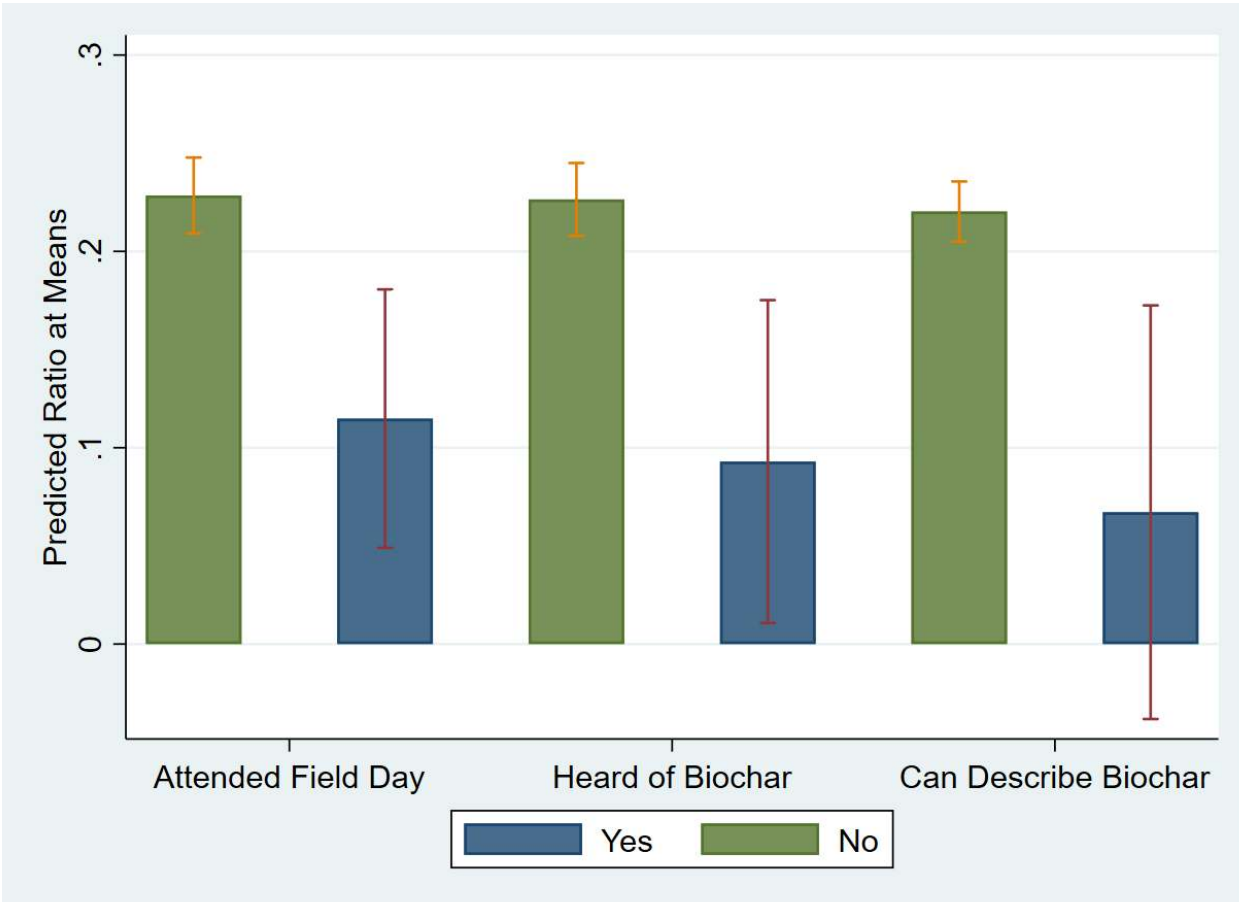


Figure 3: Cumulative Distribution: Biochar (1KG) - DAP (5KG) WTP Ratio



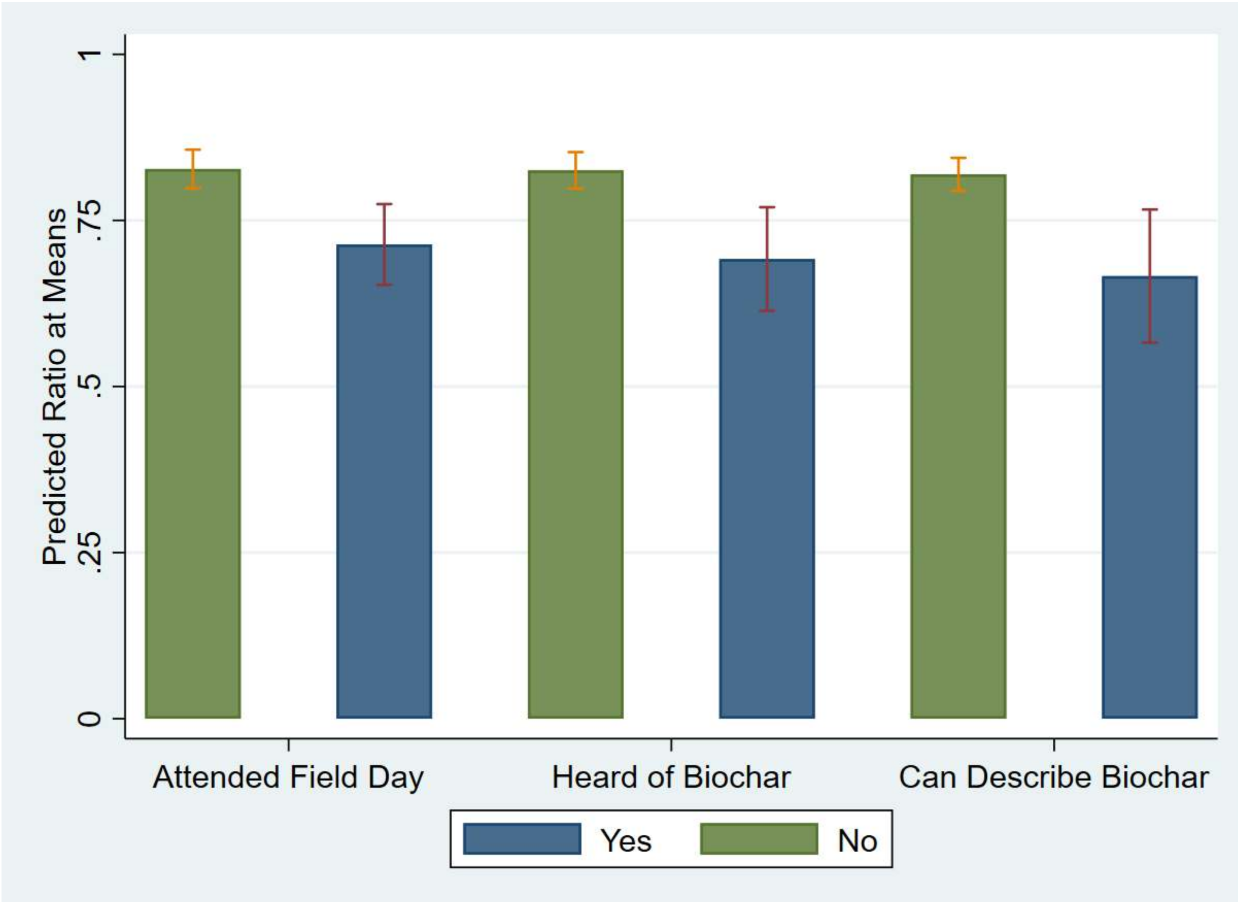
Notes: Example village demonstrating the negative correlation of randomly sampled households between distance to field day site and attendance.

Figure 4: Field Day Site Example



Notes: Predicted ratios with all regressors set at their means. Vertical lines represent 95% confidence intervals.

Figure 5: Predicted WTP ratio of 1KG Biochar to 5KG DAP fertilizer at means



Notes: Predicted ratios with all regressors set at their means. Vertical lines represent 95% confidence intervals.

Figure 6: Predicted WTP ratio of 5KG Biochar to 5KG DAP fertilizer at means

Table 1: Farmer-Managed Plot Results (Kilograms per hectare equivalent)

Village	No inputs (Control)	Inoculants (Inoc)	NPK	Vermicompost (VC)	Biochar (BC)	BC + Inoc	NPK + BC	VC + BC	Ratio of Organics to Control[a]	Ratio of Organics to NPK[b]
1	998.2	399.5	1271.7	458	627	774.2	990.5	648.6	0.58	0.45
2	538.5	790.7	1103.3	950.4	855	626.7	1433.4	794.6	1.61	0.79
3	875	1055.6	1133.8	1103	2016.8	1180.4	3225.2	2197.6	2.03	1.56
4	448.2	846.8	636.1	986.2	941.4	1080	1097.3	1448.8	2.51	1.77
5a	1372.7	1138.2	2115	1557.1	1696.3	896.8	1561.1	1516.7	1.16	0.75
5b	1289.7	1668	1513.6	1364.5	1632	895.8	1421.1	916.7	1.01	0.86
5c	1285.7	963.4	1001	1236.9	1025.4	657.2	1300.3	980.5	0.84	1.08
5d	368	233.3	325.8	494	735.3	573	913.8	1059.2	2.07	2.34
6	378.9	966	1493.1	1420.3	627.2	1562	3107.6	1266.2	2.92	0.74
7	628.6	1452.7	4057.7	2615.4	1100.9	2290	3648.6	2054.3	3.06	0.47
8	-	-	-	-	-	-	-	-	-	-
9	563.4	1035.3	2252.1	1761.8	1207.3	1127	1744.5	870.2	2.27	0.57
10	-	-	-	-	-	-	-	-	-	-
11	25.8	329	400.8	173.4	225	379.8	601.7	400	10.32	0.66
12	455.1	516.2	1147.5	347	210.5	173.9	741.5	377.6	0.68	0.27
13	652.8	691.1	938.9	370	543	578.6	562.1	757.8	0.85	0.59
14	459.4	905.7	764.5	533.3	572	696.9	880	455.4	1.13	0.68
15	151.4	218.8	812.8	1592.3	172.4	321.4	743.2	1449.6	7.08	1.32
16	1472.4	1400	2066.7	1711.2	1251.9	1526.3	2192	2004.2	1.12	0.80
17	0	901.5	1084.3	305.6	444	709.6	438.6	325.3	-	0.33
18	54.5	218.8	1513.6	590.4	386.4	380.4	380.4	355	8.15	0.29

Notes: Researcher measured values from common bean clippings in 2016. Data missing from villages 8 and 10 as the farmers harvested the crop prior to arrival of researchers. Village 5 had four separate field day hosts and sites. [a]Ratio is the average of the yields from biochar, vermicompost, and vermicompost and biochar plots divided by yield from control plot. [b]Ratio is the average of the yields from biochar, vermicompost, and vermicompost and biochar plots divided by yield from NPK plot.

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max
Individual level (n=884)				
Age[a]	48.29	16.09	19	109
Years of education[b]	7.95	3.8	0	26
Yes=1				
Attended field day (Yes=1)	.24	.43	0	1
Heard of biochar (Yes=1)	.19	.4	0	1
Can describe biochar (Yes=1)	.13	.34	0	1
Mathematics ability[c]	.56	.5	0	1
Female	.58	.49	0	1
Widow	.14	.35	0	1
Farmer	.88	.33	0	1
Household level (n=548)				
Household size[d]	5.29	3.27	0	40
Weekly food expenditures (KSh)[e]	1228.03	1774.7	0	21000
Distance to field day location (km) (IV)	.53	.35	0	1.83
Total farm area (acres)	1.06	1.06	.02	8.87
Used input (Yes=1) in past two seasons				
Compost	.37	.48	0	1
Fresh manure	.08	.28	0	1
Urea	.19	.4	0	1
DAP	.79	.41	0	1
NPK	.13	.34	0	1
CAN	.72	.45	0	1
Input use (annual kg/acre), excluding zeroes				
Compost	1443.54	2785.58	10.9	28406.02
Fresh manure	989.5	3249.04	.56	21668.62
Urea	55.06	65.14	2.54	419.76
DAP	75.42	178.79	.87	3303.91
NPK	88.62	94.48	.71	494.26
CAN	86.12	261.18	1.64	4281.11
Yes=1				
Household head is female	.45	.5	0	1
Extended family of FFD host farmer	.36	.48	0	1
Connection with NGO in past five years	.13	.34	0	1
River as primary water source	.43	.5	0	1
Electricity (grid)	.13	.33	0	1
Solar panels	.29	.45	0	1
Metal roof	.87	.33	0	1
Mud walls	.78	.42	0	1
Earth/mud floor	.72	.45	0	1
Polygamous household	.1	.29	0	1
Own cow(s)	.37	.48	0	1

Notes: [a] One women claimed she was 109 years old. [b] High max education due to sampled inividuals with graduate degrees. [c] Was able to complete a simple multiplication problem. [d] Defined as the number of individuals who spent the night at the dwelling last night. [e] 1 USD was approximatley equal to 102 KSh at the time of the survey.

Table 3: Bids for FFD Attendees and Non-attendees

Variable	(1) Field Day Attendee N	(1) Field Day Attendee Mean/SD	(2) Field Day Non-attendee N	(2) Field Day Non-attendee Mean/SD	T-test Difference (1)-(2)
DAP (1KG)	216	81.458	668	84.356	-2.898
		(32.602)		(35.761)	
DAP (5KG)	212	380.047	656	364.909	15.139
		(157.839)		(158.722)	
Biochar (1KG)	216	65.995	668	67.629	-1.633
		(39.881)		(39.946)	
Biochar (5KG)	211	266.232	660	278.424	-12.192
		(142.799)		(147.033)	
Vermicompost (1KG)	216	81.968	668	82.250	-0.282
		(48.644)		(45.372)	
Vermicompost (5KG)	208	321.851	647	324.660	-2.809
		(158.842)		(163.738)	
Biochar-DAP (1KG)	216	80.185	668	77.061	3.124
		(48.414)		(46.931)	
Biochar-DAP (5KG)	208	304.014	650	292.869	11.145
		(152.713)		(145.776)	
Biochar-Vermicompost (1KG)	216	68.935	668	68.106	0.829
		(39.609)		(39.010)	
Biochar-Vermicompost (5KG)	210	294.524	647	285.688	8.836
		(161.342)		(147.411)	
Manure (5KG)	211	132.190	659	117.904	14.285
		(133.141)		(110.950)	
Manure (25KG)	186	353.683	623	315.273	38.410*
		(281.070)		(236.787)	
Biochar (1KG) - DAP (5KG) WTP Ratio	211	0.192	653	0.204	-0.012
		(0.126)		(0.123)	
Biochar (5KG) - DAP (5KG) WTP Ratio	207	0.758	645	0.813	-0.054*
		(0.401)		(0.367)	
Vermicompost (1KG) - DAP (5KG) WTP Ratio	211	0.234	653	0.246	-0.011
		(0.142)		(0.154)	
Vermicompost (5KG) - DAP (5KG) WTP Ratio	203	0.916	633	0.946	-0.030
		(0.378)		(0.398)	

Notes: Differences in sample sizes (N) due to dropping of outliers from the analysis (See text for details). The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 4: Balance between FFD Attendees and Non-attendees

Variable	(1) Field Day Attendee N	(1) Field Day Attendee Mean/SD	(2) Field Day Non-attendee N	(2) Field Day Non-attendee Mean/SD	T-test Difference (1)-(2)
Distance to field day location (km) (IV)	216	0.358	668	0.583	-0.224***
		(0.343)		(0.328)	
Age	216	48.208	668	48.311	-0.103
		(14.559)		(16.571)	
Years of education	216	8.176	668	7.882	0.294
		(3.478)		(3.896)	
Mathematics ability (Yes=1)	216	0.602	668	0.546	0.055
		(0.491)		(0.498)	
Female (Yes=1)	216	0.551	668	0.587	-0.036
		(0.499)		(0.493)	
Widow (Yes=1)	216	0.139	668	0.139	-0.000
		(0.347)		(0.346)	
Farmer (Yes=1)	216	0.931	668	0.862	0.068***
		(0.255)		(0.345)	
Household size	216	5.472	668	5.404	0.068
		(2.570)		(3.308)	
Contact with NGO (Yes=1)	216	0.231	668	0.105	0.127***
		(0.423)		(0.307)	
Total farm area (acres)	216	1.277	668	1.051	0.226***
		(1.136)		(1.039)	
Asset index	216	0.026	668	0.022	0.004
		(0.933)		(0.959)	
Used compost (Yes=1)	216	0.500	668	0.325	0.175***
		(0.501)		(0.469)	
Used fresh manure (Yes=1)	216	0.079	668	0.094	-0.016
		(0.270)		(0.292)	
Used urea (Yes=1)	216	0.111	668	0.222	-0.110***
		(0.315)		(0.416)	
Used DAP (Yes=1)	216	0.833	668	0.799	0.034
		(0.374)		(0.401)	
Used NPK (Yes=1)	216	0.199	668	0.127	0.072***
		(0.400)		(0.333)	
Used CAN (Yes=1)	216	0.741	668	0.734	0.007
		(0.439)		(0.442)	

Notes: The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 5: First Stage Results

	Field Day Attendance			
	(1)	(2)	(3)	(4)
Distance to field day location (km) (IV)	-0.392***	-0.393***	-0.392***	-0.392***
	(0.0695)	(0.0694)	(0.0760)	(0.0759)
Village Avg DAP bid except own (IV)		-0.000896		-0.000517
		(0.00372)		(0.00377)
Total auction money (hundreds of KSh)	-0.00601	-0.00537	-0.00968	-0.00927
	(0.0319)	(0.0320)	(0.0369)	(0.0368)
Nitrate-N (g NO_3-N kg $soil^{-1}$)			-1.150	-1.146
			(0.808)	(0.808)
Phosphate-P (g $PO^{-3}{}_4$ per kg $soil^{-1}$)			21.87	21.80
			(61.29)	(61.42)
Active C (g per kg $soil^{-1}$)			-0.0500	-0.0501
			(0.0668)	(0.0669)
Constant	0.332	0.659	-0.0922	0.0971
	(0.309)	(1.391)	(0.344)	(1.393)
Instruments F-stat	31.90	15.98	26.57	13.46
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes
Household/Demographic controls	No	No	Yes	Yes
Observations	3494	3494	3486	3486

Notes: Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 6: First Stage Results (Continued)

	DAP (5KG) WTP			
	(1)	(2)	(3)	(4)
Distance to field day location (km) (IV)		-3.426		-3.352
		(2.371)		(2.471)
Village Avg DAP bid except own (IV)	-46.17***	-46.18***	-46.15***	-46.16***
	(1.924)	(1.916)	(1.866)	(1.856)
Total auction money (hundreds of KSh)	0.669	0.462	0.474	0.262
	(1.742)	(1.713)	(2.133)	(2.056)
Nitrate-N (g NO_3-N kg $soil^{-1}$)			-20.48	-21.04
			(55.67)	(54.97)
Phosphate-P (g ${PO^{-3}}_4$ per kg $soil^{-1}$)			-7555.2**	-7582.8**
			(3432.3)	(3397.7)
Active C (g per kg $soil^{-1}$)			1.089	1.014
			(5.398)	(5.273)
Constant	17500.6***	17506.3***	17509.4***	17516.4***
	(710.4)	(706.9)	(681.2)	(676.7)
Instruments F-stat	576.2	347.0	611.9	361.3
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes
Household/Demographic controls	No	No	Yes	Yes
Observations	3432	3432	3424	3424

Notes: Standard errors clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 7: Primary Estimations

	Organic Input WTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Attended field day (Yes=1)	-32.42**	-30.39**	-30.25**	-29.50**	-34.27*	-36.59**
	(15.20)	(15.36)	(15.42)	(14.03)	(18.15)	(17.47)
DAP (5kg) bid	0.312***	0.306***	0.306***	0.307***	0.308***	0.309***
	(0.0204)	(0.0200)	(0.0198)	(0.0192)	(0.0198)	(0.0201)
Total auction money (hundreds of KSh)	-7.993	-6.108	-6.076	-6.025	-6.049	-5.875
	(6.611)	(6.052)	(5.979)	(5.890)	(5.898)	(5.973)
Soil quality perception			-0.348			
			(2.683)			
Nitrate-N (g NO_3-N kg $soil^{-1}$)				272.9	269.7	266.2
				(181.4)	(185.1)	(184.6)
Phosphate-P (g $PO^{-3}{}_4$ per kg $soil^{-1}$)				-8721.3	-8419.5	-7959.7
				(8388.5)	(8463.7)	(8356.6)
Active C (g per kg $soil^{-1}$)				-32.70***	-32.65***	-33.73***
				(12.20)	(12.30)	(12.24)
Project farmer					14.65	22.10
					(18.50)	(17.55)
Info. from Ag. Ministry						11.71
						(8.616)
Participant in Ag. NGO						-11.11**
						(5.025)
First-stage F-stat	16.005	14.039	13.834	13.667	10.594	11.121
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes	Yes	Yes
Household/Demographic controls	No	Yes	Yes	Yes	Yes	Yes
Observations	3432	3432	3432	3424	3424	3424

Notes: Organic input WTP is the bid for the organic input (biochar (1KG), biochar (5KG), vermicompost (1KG), vermicompost (5KG)) divided by the bid for DAP (5KG). Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8: Primary Estimations (Continued)

	Organic/DAP WTP ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Attended field day (Yes=1)	-0.121**	-0.123**	-0.120**	-0.123**	-0.148**	-0.154**
	(0.0484)	(0.0507)	(0.0528)	(0.0507)	(0.0703)	(0.0698)
Total auction money (hundreds of KSh)	-0.00971	-0.00356	-0.00295	-0.00255	-0.00293	-0.00291
	(0.0242)	(0.0236)	(0.0236)	(0.0229)	(0.0229)	(0.0234)
Soil quality perception			-0.00764			
			(0.0139)			
Nitrate-N (g NO_3-N kg $soil^{-1}$)				1.282**	1.265**	1.257**
				(0.571)	(0.583)	(0.586)
Phosphate-P (g $PO^{-3}{}_4$ per kg $soil^{-1}$)				-18.50	-17.00	-15.78
				(14.13)	(15.06)	(15.28)
Active C (g per kg $soil^{-1}$)				-0.0433	-0.0431	-0.0460
				(0.0396)	(0.0398)	(0.0387)
Project farmer					0.0754	0.0863
					(0.0694)	(0.0663)
Info. from Ag. Ministry						0.0417
						(0.0290)
Participant in Ag. NGO						-0.0228
						(0.0246)
First-stage F-stat	31.423	27.529	27.209	26.754	20.429	21.297
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes	Yes	Yes
Household/Demographic controls	No	Yes	Yes	Yes	Yes	Yes
Observations	3416	3416	3416	3408	3408	3408

Notes: Organic/DAP WTP ratio is the bid for the organic input (biochar (1KG), biochar (5KG), vermicompost (1KG), vermicompost (5KG)) divided by the bid for DAP (5KG). Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 9: Mixed-model estimations

	Organic Input WTP	Organic/DAP WTP ratio
	(1)	(2)
Attended Field Day	-29.26*	-0.134***
	(15.23)	(0.0383)
DAP (5kg) bid	0.291***	
	(0.0184)	
Total auction money (hundreds of KSh)	-6.521	-0.00192
	(5.703)	(0.0168)
Nitrate-N (g NO_3-N kg soil^{-1})	310.7*	1.298***
	(130.5)	(0.396)
Phosphate-P (g $PO^{-3}{}_4$ per kg soil^{-1})	-8553.4	-19.15
	(6125.3)	(15.55)
Active C (g per kg soil^{-1})	-33.62***	-0.0450*
	(9.139)	(0.0227)
Constant	529.8***	0.559***
	(62.22)	(0.176)
sd(Field Day)	98.41***	0.319***
	(5.478)	(0.0167)
sd(No Field Day)	120.2***	0.331***
	(2.652)	(0.00759)
sd(Residual)	98.84***	0.282***
	(2.391)	(0.00838)
Observations	3486	3408
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes
Household/Demographic controls	Yes	Yes

Notes: Hierarchical, mixed model incorporating both fixed and random effects. *Attended Field Day* and *DAP (5kg) bid* variables here are predicted using first stage estimations. Standard errors corrected through bootstrapping (100 repetitions). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 10: Additional Estimations

	Organic Input WTP				Organic/DAP WTP ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attended field day (Yes=1)	-29.50**			-33.92**	-0.123**			-0.131**
	(14.03)			(14.06)	(0.0507)			(0.0514)
Heard of biochar (Yes=1)		-36.17**				-0.152**		
		(17.29)				(0.0598)		
Can describe biochar (Yes=1)			-40.69**				-0.171**	
			(20.07)				(0.0709)	
DAP (5kg) bid	0.307***	0.305***	0.305***	0.306***				
	(0.0192)	(0.0202)	(0.0193)	(0.0188)				
Total auction money (hundreds of KSh)	-6.025	-4.577	-4.446	-6.197	-0.00255	0.00401	0.00453	-0.00266
	(5.890)	(6.316)	(6.429)	(5.894)	(0.0229)	(0.0250)	(0.0253)	(0.0229)
Nitrate-N (g NO_3-N kg soil^{-1})	272.9	282.8	279.6*	268.7	1.282**	1.327**	1.314**	1.282**
	(181.4)	(172.0)	(165.8)	(185.9)	(0.571)	(0.538)	(0.514)	(0.577)
Phosphate-P (g $PO^{-3}{}_4$ per kg soil^{-1})	-8721.3	-10636.4	-10600.1	-8717.9	-18.50	-26.59**	-26.46**	-18.32
	(8388.5)	(7606.8)	(7969.1)	(8394.9)	(14.13)	(11.17)	(12.78)	(14.30)
Active C (g per kg soil^{-1})	-32.70***	-29.05**	-29.81**	-33.25***	-0.0433	-0.0283	-0.0315	-0.0442
	(12.20)	(13.09)	(12.90)	(12.07)	(0.0396)	(0.0445)	(0.0433)	(0.0393)
Extended family of FFD host farmer				9.908				0.0153
				(6.115)				(0.0171)
First-stage F-stat	13.667	17.039	14.092	13.588	26.754	32.730	27.710	26.532
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household/Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3424	3424	3424	3420	3408	3408	3408	3404

Notes: Standard errors clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

References

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Appendix A.1. Description of organic inputs provided to all respondents

"Biochar" is a type of charcoal that is produced from left-over plant material of field crops on farm like maize cobs and stovers, rice husks and haulms, sugarcane bagasse, coconut shells, and others. If applied to soil at the correct rate, biochar helps to improve crop production by increasing the uptake of fertilizers, manure and water.

"Vermicompost" is the end-product of the breakdown of organic matter by an earthworm, also called worm castings. It is compost produced using earthworms. If applied to the soil in the correct rate vermicompost will improve crop production because it contains substantial amounts of nutrients, has a large water holding capacity and enriches the soil with micro-organisms.

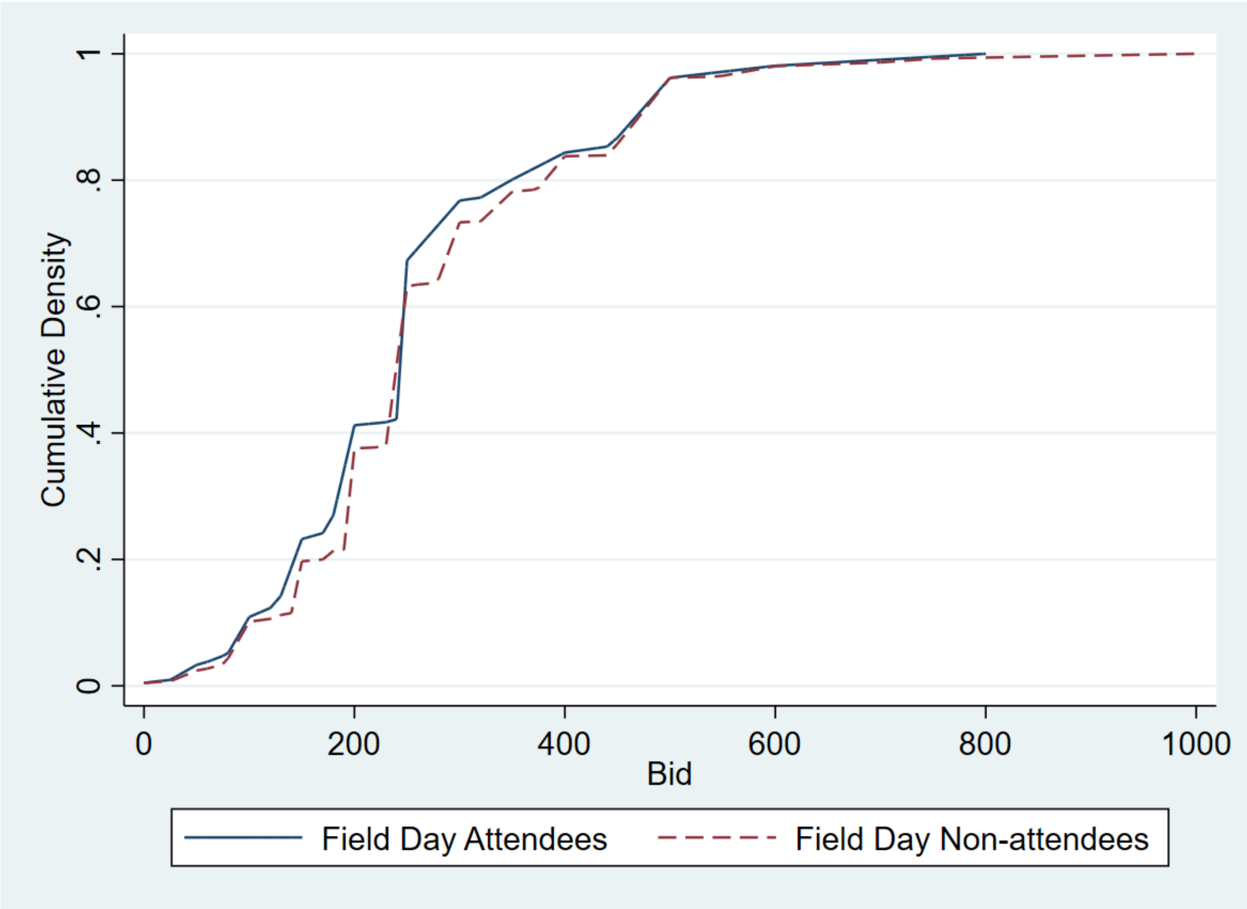

Figure A.2.1: Cumulative Distribution: Biochar (5KG) - DAP (5KG) WTP Ratio

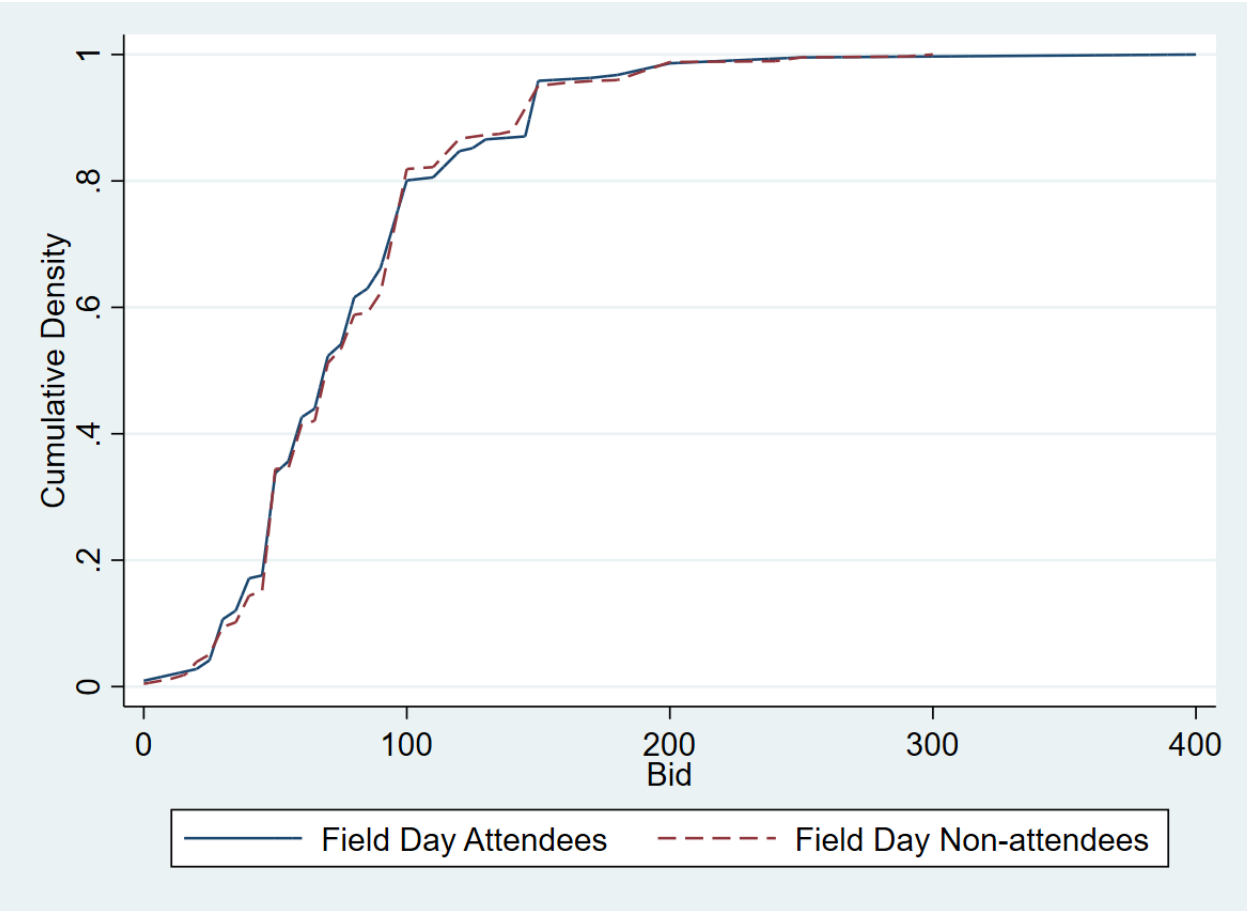

Figure A.2.2: Cumulative Distribution: Vermicompost (1KG) - DAP (5KG) WTP Ratio

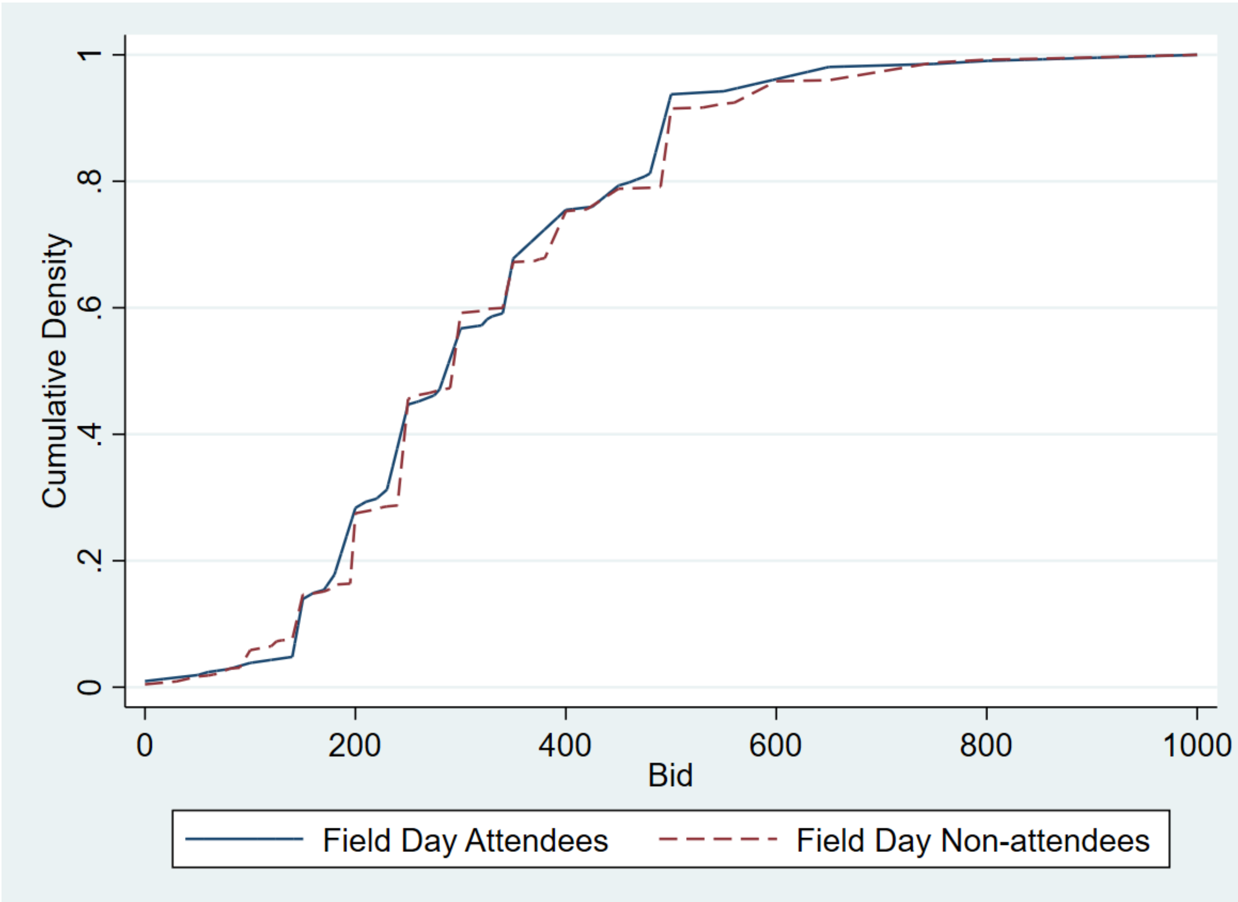

Figure A.2.3: Cumulative Distribution: Vermicompost (5KG) - DAP (5KG) WTP Ratio

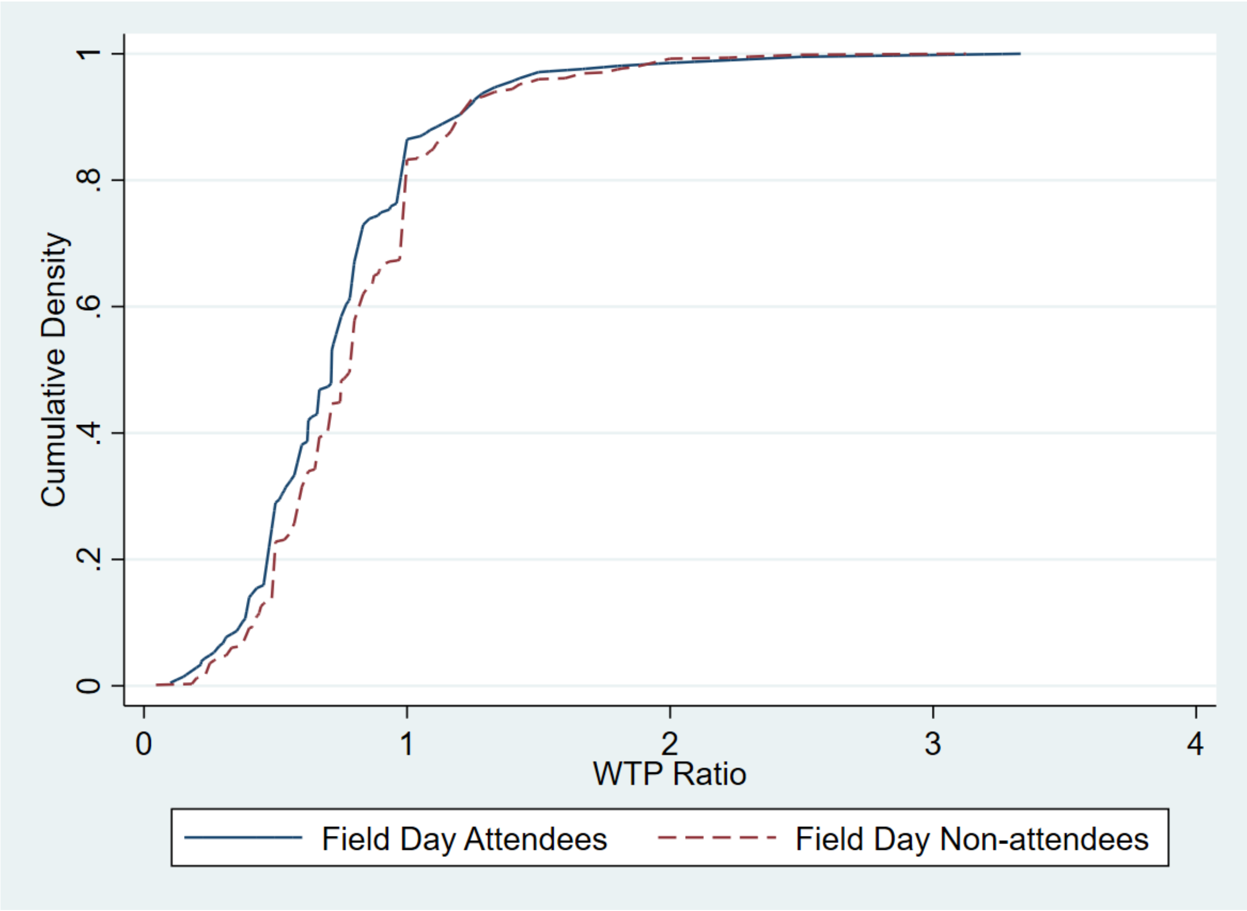

Figure A.2.4: Cumulative Distribution: Biochar (5KG) - DAP (5KG) WTP Ratio

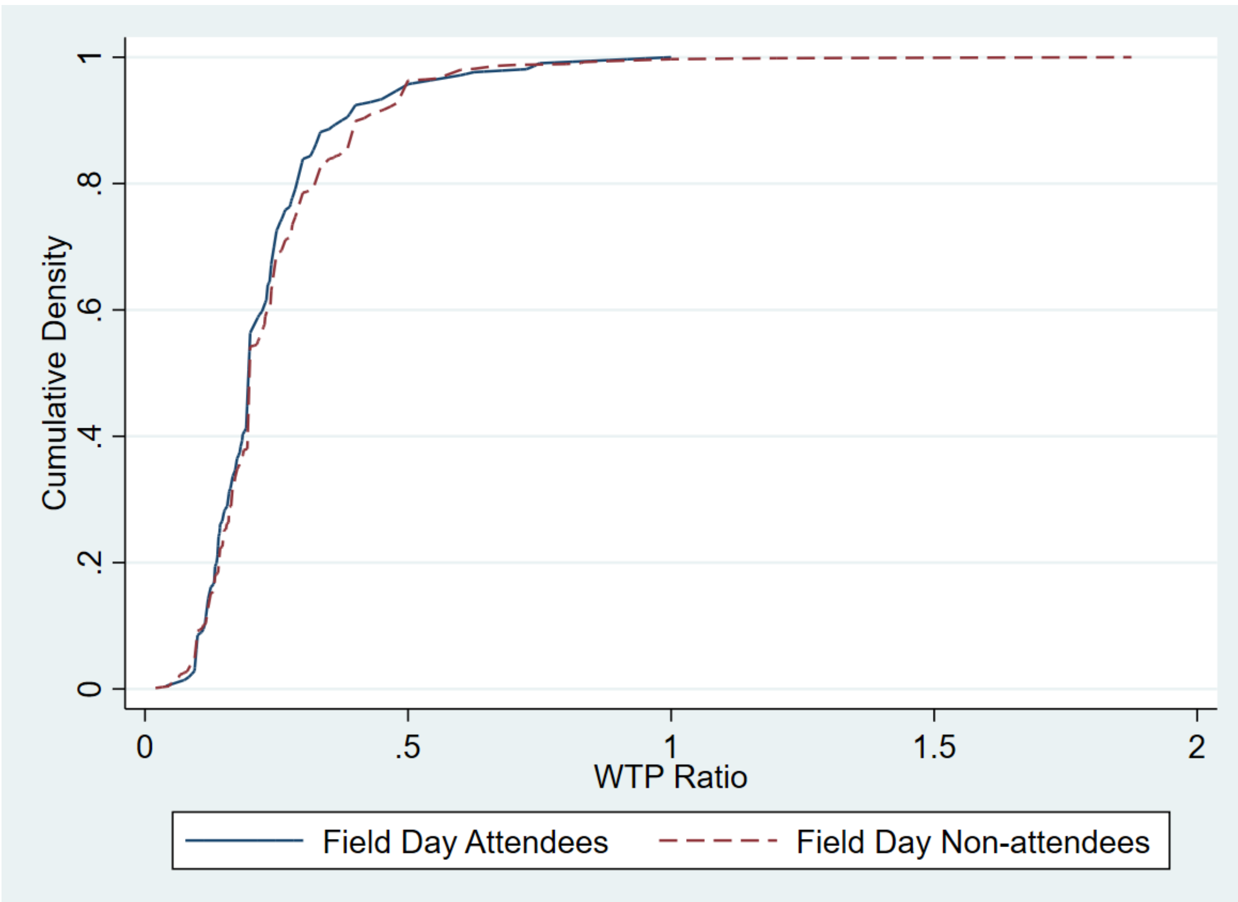

Figure A.2.5: Cumulative Distribution: Vermicompost (1KG) - DAP (5KG) WTP Ratio

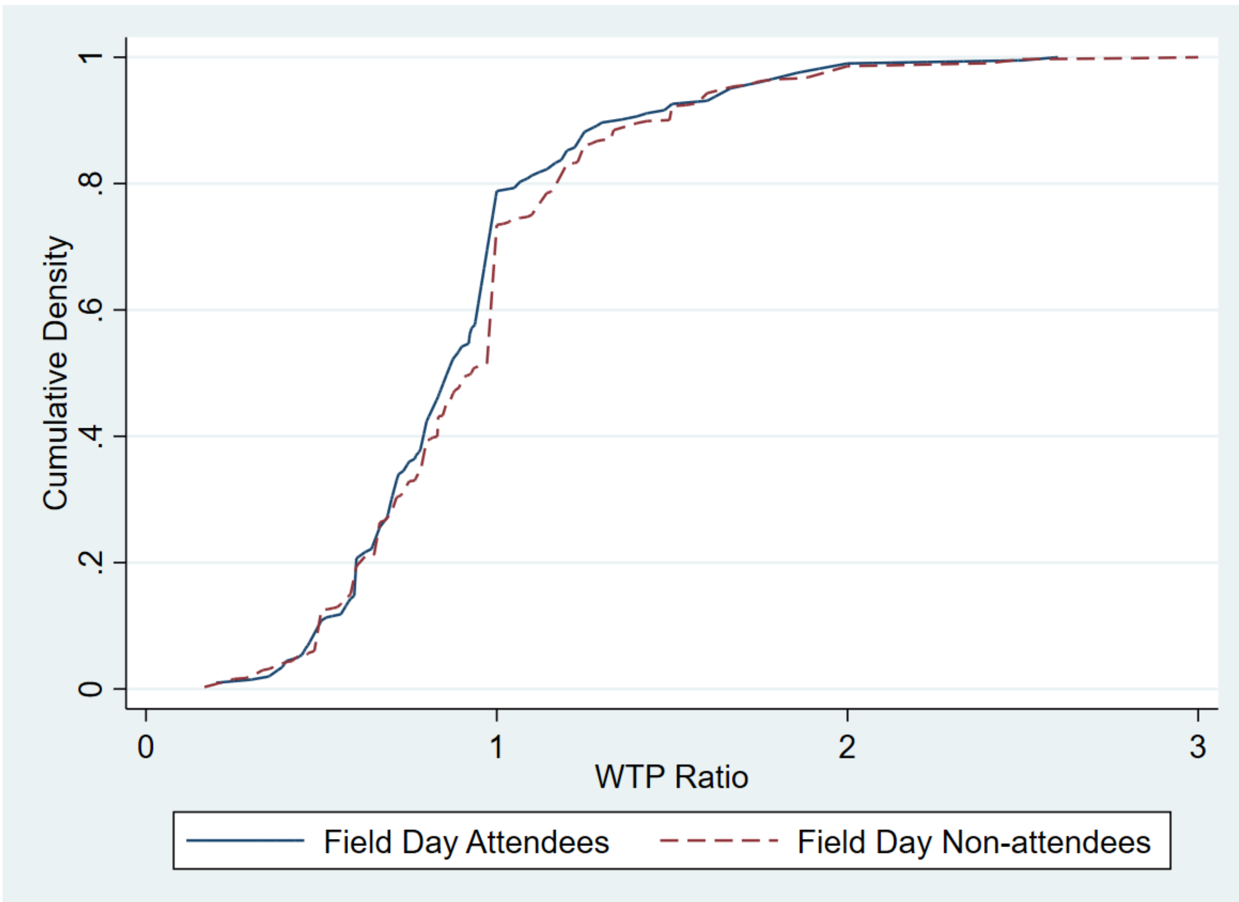

Figure A.2.6: Cumulative Distribution: Vermicompost (5KG) - DAP (5KG) WTP Ratio

Table A.3: Biochar Yield Responses

		Maize yield response compared to:					
		No input trial (ton ha^{-1})			Fertilized trial (ton ha^{-1})		
Location	Season	1	5	10	1	5	10
		(ton biochar DW ha^{-1})			(ton biochar DW ha^{-1})		
Siaya (n=288)	LR2015	0.56*	1.29*	1.96*	0.33*	0.82*	1.46*
	SR2015	0.67*	1.34*	2.07*	0.29*	0.79*	1.35*
	LR2016	0.67*	1.33*	2.14*	0.29*	0.68*	1.36*
	LR2017	0.34*	1.05*	1.68*	0.22	0.84*	1.23*
Embu (n=240)	LR2015	0.73*	1.92*	2.54*	0.43*	1.02*	1.75*
	SR2015	0.74*	1.94*	2.50*	0.43*	1.01*	1.73*
	LR2016	1.44*	2.65*	3.17*	0.58*	1.26*	1.74*
	LR2017	1.43*	2.13*	2.31*	0.63*	1.36*	1.84*
Kwale (n=96)	LR2015	0.39	1.29*	1.47*	0.13	0.66*	1.27*
	LR2016	1.11*	1.97*	2.68*	0.17	0.76*	1.39*
	LR2017	0.98*	1.74*	2.64*	0.33	0.97*	1.68*

Maize grain yield responses to different rates of soil biochar amendments compared to no-input and fertilized trails from three agro-ecosystems in Kenya over multiple growing seasons LR: Long rains season; SR: short rain season). Biochar was applied once, at the start of the experiments, incorporated along the base of planting lines. Information derived from mixed effect significance of difference test between input treatments per study area. Data reported by the International Institute of Tropical Agriculture, the Swedish University of Agricultural Sciences, and the Royal Institute of Technology in Stockholm. *$p < 0.05$.

Table A.4: Monte Carlo Simulation Results for Biochar PV

Parameter	Mean (Std. Dev)
Discount rate	0.051
	(0.028)
Maize price (KSh per ton)	24070.14
	(2422.08)
Biochar yield impact (tons per hectare)	0.501
	(0.291)
Biochar app. rate (constant - tons per hectare)	1.0
Total two-year biochar present value (KSh per kilo)	44.93
	(26.71)

Results from Monte Carlo estimations with 10,000 repetitions.

Table A.5: Wild Bootstrap P-values (Organic WTP)

	(1)	(2)	(3)	(4)	(5)	(6)
Village-level cluster p-values	0.033	0.048	0.050	0.039	0.063	0.039
Wild bootstrap p-values	0.026	0.034	0.036	0.024	0.041	0.031
HH/Demographic Vars.	No	Yes	Yes	Yes	Yes	Yes
Village/Enumerator/Input/Svy. Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Dep. Variable: Bid (Ksh) for organic inputs. Numbered estimations correspond to those on Table 7. Wild bootstrapped p-values shown as correction for small number of village-level clusters (18) with 999 repetitions per estimation.

Table A.6: Wild Bootstrap P-values (WTP Ratio)

	(1)	(2)	(3)	(4)	(5)	(6)
Village-level cluster p-values	0.012	0.015	0.024	0.018	0.038	0.029
Wild bootstrap p-values	0.004	0.015	0.031	0.016	0.032	0.031
HH/Demographic Vars.	No	Yes	Yes	Yes	Yes	Yes
Village/Enumerator/Input/Svy. Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Dep. Variable: WTP ratio for organic inputs relative to DAP. Numbered estimations correspond to those on Table 8. Wild bootstrapped p-values shown as correction for small number of village-level clusters (18) with 999 repetitions per estimation.

Table A.7: First-stage of Knowledge Estimations

	Attend Field Day		Heard of Biochar		Can Describe Biochar	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to field day location (km)	-0.400***	-0.392***	-0.326***	-0.321***	-0.290***	-0.281***
	(0.0765)	(0.0760)	(0.0561)	(0.0577)	(0.0547)	(0.0551)
DAP (5kg) bid	0.0000704		0.0000120		-0.0000170	
	(0.0000777)		(0.000117)		(0.0000841)	
Total auction money (hundreds of KSh)	-0.00976	-0.00968	0.0323	0.0320	0.0315	0.0312
	(0.0387)	(0.0369)	(0.0370)	(0.0372)	(0.0348)	(0.0341)
Nitrate-N (g NO_3-N kg soil^{-1})	-1.442	-1.150	-0.899	-0.636	-0.882	-0.592
	(1.059)	(0.808)	(0.889)	(0.758)	(1.074)	(0.933)
Phosphate-P (g $PO^{-3}{}_4$ per kg soil^{-1})	29.57	21.87	-28.80	-35.51	-24.77	-26.28
	(64.67)	(61.29)	(32.02)	(30.64)	(29.91)	(28.09)
Active C (g per kg soil^{-1})	-0.0361	-0.0500	0.0714	0.0619	0.0450	0.0415
	(0.0653)	(0.0668)	(0.0481)	(0.0494)	(0.0550)	(0.0542)
Constant	-0.0918	-0.0922	-0.357	-0.387	-0.396	-0.435
	(0.368)	(0.344)	(0.370)	(0.338)	(0.376)	(0.341)
Instrument F-stat	14.317	26.571	20.971	30.891	14.882	26.008
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes	Yes	Yes
Household/Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3424	3486	3424	3486	3424	3486

Notes: Standard errors clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.8: Alternative WTP Ratio (DAP Average Bid)

	Organic/DAP WTP ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Attended field day (Yes=1)	-0.157**	-0.156**	-0.155*	-0.156**	-0.182*	-0.194*
	(0.0741)	(0.0781)	(0.0815)	(0.0772)	(0.105)	(0.103)
Total auction money (hundreds of KSh)	-0.0186	-0.00688	-0.00668	-0.00552	-0.00591	-0.00592
	(0.0374)	(0.0365)	(0.0362)	(0.0350)	(0.0349)	(0.0357)
Soil quality perception			-0.00253			
			(0.0201)			
Nitrate-N (g NO_3-N kg $soil^{-1}$)				2.056**	2.039**	2.023**
				(0.979)	(0.993)	(0.995)
Phosphate-P (g $PO^{-3}{}_4$ per kg $soil^{-1}$)				-31.99	-30.43	-27.99
				(24.26)	(25.12)	(25.37)
Active C (g per kg $soil^{-1}$)				-0.0887	-0.0885	-0.0941
				(0.0592)	(0.0593)	(0.0578)
Project farmer					0.0777	0.0987
					(0.106)	(0.104)
Info. from Ag. Ministry						0.0844*
						(0.0471)
Participant in Ag. NGO						-0.0450
						(0.0350)
First-stage F-stat	31.423	27.514	27.197	26.737	20.414	21.277
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes	Yes	Yes
Household/Demographic controls	No	Yes	Yes	Yes	Yes	Yes
Observations	3416	3416	3416	3408	3408	3408

Notes: Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Notes: Organic/DAP WTP ratio is the bid for the organic input (biochar (1KG), biochar (5KG), vermicompost (1KG), vermicompost (5KG)) divided by the average of the bid for DAP (1KG) and DAP (5KG). Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A.9: Falsification Test: Fake FFDs

	F-statistic	P-value
Actual First Stage	26.57	0
Simulation Results:		
Mean	1.47	.47
Std. Dev.	2.37	.3
Median	.57	.46
75th percentile	1.73	.21
90th percentile	3.99	.06
95th percentile	6.26	.02

Notes: 10,000 first-stage estimations with random "fake" homesteads serving as field day locations chosen within village. Specification used is found in Column 3 of Table 3. Actual first-stage statistics as found in Table 3 are in the first row above. Simulation results for fake field day locations are in the lower panel. The statistics demonstrate that distances to random homesteads that serve as fake field day locations are generally not strongly correlated with field day attendance, showing that our IV genuinely represents a strong correlation between distance to and attendance at the field day.

Table A.10: Alternative First-stage with Distance to Village Center

	Field Day Attendance			
	(1)	(2)	(3)	(4)
Distance to village center (km)	0.0922	0.113*	0.108	0.0717
	(0.0657)	(0.0611)	(0.0634)	(0.0558)
Total auction money (hundreds of KSh)	0.0169	0.0149	0.0147	0.00902
	(0.0346)	(0.0442)	(0.0444)	(0.0413)
Nitrate-N (g NO_3-N kg soil^{-1})			-1.076	-0.948
			(0.858)	(0.729)
Phosphate-P (g $PO^{-3}{}_4$ per kg soil^{-1})			27.73	33.04
			(70.64)	(68.97)
Active C (g per kg soil^{-1})			-0.0377	-0.0286
			(0.0642)	(0.0655)
Project farmer				0.732***
				(0.0478)
Constant	0.0936	-0.481	-0.469	-0.311
	(0.317)	(0.353)	(0.343)	(0.326)
Instrument F-stat	1.972	3.430	2.890	1.653
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes
Household/Demographic controls	No	Yes	Yes	Yes
Observations	3494	3494	3486	3486

Notes: Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A.11: Alternative First-stage with Family of FFD Host as Additional Instrument

	Field Day Attendance			
	(1)	(2)	(3)	(4)
Distance to field day location (km)	-0.392***	-0.390***	-0.391***	-0.307***
	(0.0691)	(0.0746)	(0.0760)	(0.0698)
Extended family of FFD host farmer	0.00275	0.0106	0.00949	0.0477*
	(0.0288)	(0.0271)	(0.0272)	(0.0241)
Total auction money (hundreds of KSh)	-0.00602	-0.00899	-0.00961	-0.0102
	(0.0320)	(0.0365)	(0.0369)	(0.0363)
Nitrate-N (g NO_3-N kg $soil^{-1}$)			-1.164	-1.020
			(0.806)	(0.720)
Phosphate-P (g $PO^{-3}{}_4$ per kg $soil^{-1}$)			21.44	27.69
			(61.74)	(63.91)
Active C (g per kg $soil^{-1}$)			-0.0503	-0.0420
			(0.0671)	(0.0693)
Project farmer				0.587***
				(0.0656)
Constant	0.331	-0.119	-0.0940	-0.0586
	(0.309)	(0.348)	(0.346)	(0.334)
Instrument F-stat	16.09	13.72	13.26	11.39
Fixed effects (Village/Enumerator/Input/Svy. Month)	Yes	Yes	Yes	Yes
Household/Demographic controls	No	Yes	Yes	Yes
Observations	3490	3490	3482	3482

Notes: Standard errors clustered at the village level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.