Pesticides: What you don't know *can* hurt you

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Abstract: Agricultural producers have imperfect knowledge of the health risks posed by many agricultural inputs. This paper explores the effects of information on demand for substitutes or new risk-mitigating technologies using a randomized controlled trial in Zambia. Information had an insignificant effect on demand for personal protective equipment, but a significant effect on demand for substitutes, lower toxicity pesticides. The treatment group was greater than three times more likely to substitute a high toxicity pesticide for a low toxicity pesticide after receiving training. What farmers do not know can hurt them through lower demand for less risky substitutes.

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I. Introduction

A large empirical literature demonstrates that what you don't know can hurt you. Both consumers and producers shift demand for commodities and inputs in response to changes in health or safety knowledge. Empirical applications on the consumer demand side include automobile demand (Peltzman, 1975; Winston and Mannering, 1984; McCarthy, 1996; among others), food demand (Piggott and Marsh, 2004, and Lusk and Coble, 2005, among others), and safe sex (Gong, 2014), among others. An equally robust literature among producers includes applications for pollution (Zivin and Neidell, 2012), mining (von der Goltz and Barnwal, 2014), and fertilizer application (Conway and Pretty, 1988).

One area of growing importance where health risks and information may play important roles in demand is pesticide use in developing countries. Pesticide use in developing countries is increasing (Williamson et al., 2008) and Sheahan and Barret (2017) show that pesticide use in SSA is higher than previously expected. Pesticides offer large benefits in agricultural pest control (Crissman et al., 1994; Pingali et al., 1994). They also present potentially large environmental and human health costs (Tilman et al., 2001; Tilman et al., 2002) including long-term health risks like cancers, Parkinson's disease (Gorell et al., 1998), and neuropsychological effects (Savage et al., 1988).

No population faces larger health risks than small-scale farmers that work directly with the chemicals. The risks they face have two primary inputs: personal protective equipment (PPE) and toxicity. PPE (e.g., rubber boots or gloves) can reduce health risks by limiting or preventing pesticide exposure. Toxicity represents the potential hazard or harm of a chemical (WHO, 2010) and farmers can decrease their health risks by using less toxic pesticides. Pesticide related illnesses are a real health risk for farmers in developing countries (Sheahan et al., 2016; WHO, 1990; Crissman et al., 1994; Pingali et al., 1994), many of whom apply highly toxic class Ib[1] pesticides that have very serious health risks from exposure (WHO, 1990), and use incomplete PPE (Maumbe and Swinton, 2003; Ntow et al., 2006; Negatu et al., 2016; Matthews et al., 2003; Dasgupta et al., 2007).

In response to changes in health information, two behavioral responses have been well-documented in the literature including substituting to lower risk products or adopting risk-mitigating technologies. Despite potentially large benefits in preventing illnesses, previous research shows generally low adoption of health inputs (Dupas, 2011) including slow uptake by at-risk households of preventative repeated use health inputs like bed nets (Dupas, 2014) and water treatment methods (Ashraf et al., 2010). These inputs provide large health benefits in preventing malaria and diarrhea, yet those benefits are fully achieved only after an upfront investment and consistent use. One possible explanation for low adoption is a lack of health risk information, which may be especially important for new, complicated technologies (Jack, 2013).

However, previous research shows mixed evidence of information's impacts on health demand. Madajewicz et al. (2007) find that information on water safety and the potential health

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[1] Throughout this paper, we use World Health Organization (WHO) human health risk classifications of toxicity (WHO, 2010).

effects from unclean water led to safer water behaviors. Fitzsimmons et al. (2012) find that information on infant nutrition and health can improve infant feeding practices. There is also evidence that the effects of information are stronger when individuals have priors that are substantially different from the message presented by new information. Dillon et al. (2014) find significant effects of health information on labor productivity, especially for farmers that are surprised by the information. Gong (2014) shows that HIV test result information has stronger effects on behavior when people are surprised by them.

Yet, other studies show little effect of information on health behaviors. Meredith et al. (2013) conduct a series of controlled experiments and conclude that information by itself does not impact household investment in preventative health goods. Dupas (2011) offers a selected review of health behavior literature in developing countries. She notes that although households often spend a large share of their income on health, they do not often invest in preventative goods, and she mentions that information can impact behavior, but information alone is not always enough.

This paper uses a block randomized control trial among tomato producers to estimate demand for personal protective equipment after experiencing a pesticide training course. We also estimate willingness to pay for different types of pesticides, varying toxicity using contingent demand data that was collected at the baseline and endline of the randomized control trial. Information had an insignificant effect on demand for personal protective equipment, but a significant effect on demand for substitutes, lower toxicity pesticides. The treatment group was greater than three times more likely to substitute a high toxicity pesticide for a low toxicity pesticide after receiving training. What farmers do not know can hurt them and lower demand for less risky substitutes.

The paper is presented as follows. Section II presents background information about pesticide use and the Zambian context. Section III outlines the data and experiment. Section IV presents the empirical strategy and main results for PPE. Section V discusses the empirical strategy and main results for pesticide demand. Section VI concludes.

II. Background

Vegetable production, and tomato production in particular, is an important source of income for many smallholder farmers in Zambia, with gross margins more than 100 times that of maize, the dominant field crop (Hichaambwa et al., 2015). These higher returns come with nearly ubiquitous crop loss risks from pests; pest pressure was the leading reason cited for horticultural crop loss by a wide margin (Snyder et al., 2015). Two commonly reported pests are bollworms and nematodes, which can dramatically reduce the share of tomato production that meets the informal market standards for quality.

To mitigate the risks of crop loss, Zambian farmers overwhelmingly turn to synthetic pesticides and, thus, subject themselves to large acute and chronic health risks. Zambian farmers have access to and often apply several extremely toxic pesticides including Monocrotophos, Methamidophos, and Umet, each classified by the World Health Organization (WHO) as toxicity class Ib. Importantly, farmers also have access to and regularly apply pesticides that are unlikely to be toxic in regular use (WHO class U products). The available WHO class U products are labelled for controlling the same pests as the WHO class Ib products, thus substitution across toxicity classes is feasible for most pests without meaningful decreases in pest control efficacy.

The potential health risks from pesticide use are realized only when farmers become exposed to pesticides, and using PPE such as rubber boots, gloves, a cotton work suit, and a dust mask can greatly reduce the probability of acute poisoning. Keifer (2000) reviewed 17 small sample studies of pesticide exposure and found PPE items to decrease pesticide exposure in uncontrolled field environments. Yet, in Zambia, and in much of SSA, complete protection from pesticide exposure through PPE use is exceedingly rare. There may be several reasons for the low PPE use rates including lack of PPE availability and high prices (Matthews et al., 2008), and cultural and social norms (Feola and Binder, 2013). Information may also be important constraint. The literature is mostly unified in its recommendation to improve farmer safety practices by providing farmers with information through trainings (Matthews et al., 2003; Hashemi et al., 2011; Ntow et al., 2006; Tijani et al., 2006).

III. Data and Experimental Design

Three Agricultural Camps[2] in Mkushi District, Zambia were selected as our study area for the region's high concentration of tomato farmers who regularly use highly toxic pesticides. We identified 711 farmers tomato farmers that grew and sold tomatoes in the year prior to the baseline survey. To facilitate a village-level intervention, 32 Enumeration Areas (EAs) were created using spatial data and natural delineations (e.g., rivers and hills) as boundaries EAs whenever possible[3]. Sixteen farmers were randomly selected within each EA yielding a total sample of 512 farmers.

There are potentially large selection challenges to overcome when assessing the impact of information on behavior. Individuals may choose what production information to attend to and learn from (Hanna et al., 2014) and individuals are more likely to accept greater search costs to acquire information they care deeply about. Thus, for a particular good, the information one has (and their subsequent knowledge) is likely correlated with demand through unobservable preferences. In our case, a farmer's choice to acquire information is likely related to their health preferences which also affect demand for PPE and pesticides by toxicity classes. To address the identification challenge posed by unobservable farmer preferences, farmers were randomly assigned – at the enumeration area (EA) level – to receive pesticide safety information, thus making it completely exogenous to the farmers' behaviors[4].

To improve sample balance and to increase statistical power in our effect estimates, we first stratified the EAs into pairs by their mean pesticide knowledge scored over twelve true/false questions (Bruhn and McKenzie, 2009). The impact of new information likely depends on what farmers already know and how well they know it, thus baseline knowledge is an important

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[2] To allocate resources, the Zambian government divides each district into multiple Agricultural Camps.

[3] We could not use existing village structures as the unit of randomization due to variations in size and inconsistent farmer definitions of what a "village" was. Many farmers defined their "village" as their household compound consisting mostly of family members, and many insisted that they were not part of a broader village structure containing many households.

[4] This design has the added benefit of controlling for other possible mechanisms through which knowledge may be endogenous to demand. For instance, a farmer's unobservable cognitive ability may affect their knowledge as well as their demand for a good.

determinant of any information effects. Further, pesticide knowledge at the EA level is likely correlated with access to information, which is, in turn, likely to be associated with health beliefs and behaviors. Thus, blocking over pesticide knowledge prior to randomization likely reduces across-EA variance between the treatment and control groups in farmer information sets.

Detailed interviews were conducted both before (baseline) and after (endline) the information intervention. We developed the baseline questionnaire after (i) 40 semi-structured interviews that focused on pesticide purchasing behaviors, mixing and application techniques, and information sources; (ii) four observations of in-field pesticide applications; and (iii) visits to 16 pesticide retail outlets to catalogue available pesticides and to talk with agronomists and salespeople. We obtained information on household and farmer demographics, pesticide purchases and knowledge, extension and information sources, acute symptoms experienced from pesticide use, and pesticide choices from two contingent demand experiments (described below in section V.D). Approximately three months after the baseline (and approximately two months after the information intervention for the treatment group) we conducted an endline survey that closely mirrored the baseline, but included two additional modules to assess farmer WTP for protective equipment (described in section IV.A below).

A. Sample balance

The sample for analysis is a panel of 413 tomato farmers, which reflects 7 observations of attrition, 28 observations trimmed for outlying data[5], and 64 observations (4 EAs or two blocks) trimmed for large imbalances between treatment and control groups. The attrition observations are statistically similar to the non-attrition farmers and well balanced over treatment and control groups. Table A1 in the appendix highlights the improved sample balance after trimming. The control group had significantly more farmers with business income prior to trimming, which is potentially problematic as income will affect demand for PPE and pesticide choices. Further, business income may be correlated with access to certain types of information and access to pesticides and PPE, which could impact farmer knowledge and familiarity with products, and therefore affect demand. To help correct for these potential problems, we trimmed our sample to exclude the two blocks (4 EAs, 13% of our sample) with the largest differences in business income between treatment and control groups. After trimming, there are no longer significant differences in business income and the number of advice sources between treatment and control groups. For the remainder of this paper we present results using the trimmed sample of 413 farmers. Key full sample results are included in the appendix section 2 as a robustness check, and we note any meaningful differences between the two samples in the text.

B. Information intervention

The overarching goal of the information intervention was to improve pesticide risk knowledge. Semi-structured interviews and field observations conducted prior to the baseline revealed two key risky pesticide behaviors that became the primary focal points of the information intervention. First, most farmers used little to no PPE when working with pesticides. Many farmers had experienced acute illnesses from pesticides and some mentioned "being careful" when

[5] Outliers are defined as three times the standard deviation from the mean in the following potentially important variables affecting demand; first principal component of 12 durable assets owned, BDM bids for gloves or masks, the area of tomatoes planted, or the number of pesticides applied.

working with pesticides, but PPE use was low even for those farmers. Second, farmers did not understand pesticide toxicity labels and many did not differentiate products by health risks. More than one farmer said, “poison is poison,” implying a flat risk perception where all pesticides are perceived to be equally toxic. Thus, our two main points of emphasis in the information intervention were (i) to teach farmers about pesticide toxicity and how to identify toxicity labels, and (ii) to emphasize the importance of PPE in reducing pesticide exposure and to teach farmers how to effectively protect themselves while working with pesticides. A secondary goal was to better acquaint farmers with a subset of the locally available pesticides, particularly class U (low toxicity) options.

Information volunteered by farmers during baseline interviews suggested that many farmers perceived a positive relationship between a pesticide’s price and its efficacy in controlling pests – i.e., higher priced pesticides were perceived to be stronger, more effective products. The literature documents similar price-quality perceptions for products unrelated to pesticides (Zeithaml, 1988; Wolinsky, 1983; Bagwell and Riordan, 1988), and shows that better product information weakens the quality signal indicated by price (Zeithaml, 1988; Bagwell and Riordan, 1988). Therefore, we included a third training objective to combat this apparent flaw in farmer pesticide knowledge with information refuting a relationship between pesticide prices and efficacies.

Pesticide safety information was delivered through a farmer-to-farmer training program and a personalized letter. Farmer-to-farmer training programs are a common, low-cost extension method that can significantly increase farmer knowledge and technology adoption (BenYishay et al., 2016). Programs typically rely on existing social networks to share information within a community. Beaman and Dillon (2016) test the diffusion of information through social networks by randomly assigning farmers to receive information on composting. They find that farmers in treatment villages have significantly higher composting knowledge after the information was distributed, and that social connectivity matters in information diffusion as farmers with shorter social distance to the trained farmers learned more (Beaman and Dillon, 2016). We designed the experiment to test the combined impact of both information interventions on PPE demand, and we cannot test the impacts of each mechanism separately. We combined the two interventions into a single treatment to increase the expected impact, and subsequently increase power. The final sample and design had a minimum detectable effect size of 0.3 for gloves and 0.4 for masks[6] at a power level of 0.8 and a significance level of 0.05.

We worked with Ministry of Agriculture and Livestock (MAL) representatives to implement the training program as follows. Farmers in each EA voted privately for one farmer to represent them as “lead farmers” and the majority vote recipient attended a two-day pesticide safety training led by MAL in a nearby town. Lead farmers were compensated for their travel and time at the training. Upon completing the training, the lead farmers returned home to conduct local trainings of the same content for the other farmers in their EAs. We gave lead farmers a cash stipend to serve a meal at their local trainings to encourage training attendance. Lead farmers also

[6] Gloves and mask bids varied in their intra-class correlation coefficients, hence the difference in their minimum detectable effect sizes.

received sample pesticides and protective equipment so they could easily demonstrate toxicity labels and PPE use.

In addition to the local trainings, lead farmers were directed to send letters through the informal mail system to each of the farmers in their EAs. We provided all necessary materials for the letters, including a one-page color summary of pesticide safety content in English (shown in Figure A2 in the appendix) and the local language, and materials to write personalized notes. Lead farmers were directed to include a brief, handwritten note to each individual encouraging them to consider carefully the information within. The intervention was largely successful in reaching targeted farmers; seventy eight percent of the treatment group received information at the training or through the letter, though only 30% received information from both sources[7]. The experimental design effectively limited spillover as just 10 control group farmers received information directly from the training or letter.

IV. Protective Equipment Demand

A. Eliciting demand for protective equipment: Becker-DeGroot-Marschak mechanisms

Two Becker-DeGroot-Marschak (BDM) mechanisms were implemented at the conclusion of the endline survey to elicit demand for PPE: one for protective gloves and one for dust masks. BDM mechanisms reveal a point estimate of willingness-to-pay (WTP) for each farmer and Davis and Holt (1993 p 461) emphasize that they are incentive compatible experiments for expected utility maximizers.

The BDM mechanism procedures closely followed Berry et al. (2015) but were modified to our study context and according to pretesting results. Farmers played a practice round of the BDM mechanism for a bar of soap before playing for the two protective items. We randomly assigned the order in which farmers saw PPE items: half of the sample played the BDM mechanism for gloves first and the other half played the BDM mechanism for a dust mask first. Each item had the same script and procedure (a sample script and pictures of the gloves and masks are included in appendix Figure A1). To begin each BDM mechanism round, we allowed the farmer to hold and interact with the relevant item in its original packaging and asked them to report the maximum price they were willing to pay. After the farmer offered their bid b, the interviewer reviewed possible outcomes to confirm that the farmer understood the game, and gave the farmer the opportunity to adjust their bid if they so desired. When the farmer settled on their best WTP bid, the farmer drew a price card d from the relevant card deck[8]. If $b > d$ (i.e., the farmer had a "winning" bid), then the transaction took place immediately.

[7] Figure A3 in the appendix shows a detailed breakdown of information receipt.

[8] Each item had its own price distribution and corresponding card deck. We chose the price distributions based on bids offered during pretest interviews. We used uniform distributions in one Zambian Kwacha (ZMW) increments. For masks, the distribution was 1 to 10 ZMW and for gloves, the distribution was 1 to 15 ZMW. We deliberately left 0 ZMW out of the distributions to eliminate the possibility of a farmer winning an item for free. We were concerned that word of 'free' items might spread quickly through our research area and adversely affect future BDM mechanism bids, while requiring farmers to pay even one kwacha would greatly reduce that risk. The next section contains robustness checks on random price draws.

B. Empirical model

The first empirical objective is to identify the causal effect of pesticide safety information on WTP for PPE. To avoid the potential endogeneity problems of information receipt discussed in section III we rely on the random assignment of pesticide information to identify the causal effects of information on WTP by estimating intention-to-treat (ITT) regressions. There may be variation in treatment effects across observable characteristics. Therefore, we test for heterogeneous effects of information with the following specification:

$$WTP_{ijk} = \beta_0 + \beta_1 Treat_{ij} + \beta_2 Cov_i + \beta_3 \left[Treat_{ij} * Cov_i\right] + \textstyle\sum_l \delta_l X_{li} + B_k + \varepsilon_{ij} \qquad (1)$$

where WTP_{ij} is the willingness-to-pay bid for a PPE item for farmer i in EA j in block k. $Treat_{ij}$ is the random treatment assignment variable and Cov_i is the covariate across which we test for heterogeneous effects. We estimated (1) five times, once for each of the following covariates: an indicator variable for low (i.e., bottom 30th percentile) knowledge of PPE benefits, an education indicator variable equal to one if the farmer completed grade seven[9], a tomato experience variable defined as the number of years in the last 10 that a farmer grew tomatoes, the number of class Ib pesticides applied at baseline, and the number of class U pesticides applied at baseline. To increase precision of the treatment effect estimates we included block k fixed effect B_k (Bruhn and McKenzie, 2009) that controls for baseline EA-level mean knowledge and partial variation in other variables correlated to that knowledge (discussed in section III). We also included five control variables X_{li} which are the first principal component of 17 asset ownership variables and land ownership, a farmer age variable, a sex indicator variable equal to one if female, a tomato experience variable defined as the number of years in the last 10 that a farmer grew tomatoes, and a control variable for the randomized order in which the BDM games were played (equal to one if masks were first).

As is common in RCT analysis, we assume the error term ε_{ij} is correlated within EAs – our level of randomization – but uncorrelated across EAs. Therefore, we present cluster robust standard errors at the EA level that provide more accurate inference of treatment effects as discussed by Bertrand et al. (2004) and employed by Keskin et al. (2016). Equation (1) is estimated by linear projection model; however, there are a nontrivial share of corner solution bids equal to zero (approximately 20% of the bids for each item). While imperfect in the face of corner solution data, linear projection models can still provide good estimates of the average partial effects of explanatory variables (Wooldridge, 2010 p 668)[10].

The effects of information on WTP are captured by the estimators $\widehat{\beta_1}$ and $\widehat{\beta_3}$. The common literature recommendation that information is needed to improve pesticide safety behaviors

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[9] Grade 7 is a natural cut-off in education in Zambia, as there is a national level examination at the end of grade 7 that pupils must pass to advance to grade 8.

[10] As a robustness check to OLS, we also estimate (1) by Tobit maximum likelihood estimation that explicitly accounts for the corner solution bids where $WTP_{ij} = 0$. Greene (2002) found that Tobit fixed effects estimates were generally consistent thus the incidental parameters problem is not a concern. Given the large share of corner solution responses, we also create an indicator variable equal to one if $WTP_{ij} > 0$ to test whether treatment assignment affected the probability that a farmer offered a positive bid (Table A3 in the appendix).

implicitly expects a positive effect of information. However, when accounting for possible health input substitution between PPE and pesticide toxicity, there is no clear expected sign for information effects on WTP. If PPE and pesticide toxicity are substitutes in health production, then information on relative pesticide toxicity may have negative effects on WTP for PPE through a risk substitution effect. If farmers hold priors that all pesticides are highly toxic, then improved knowledge of relative pesticide health risks could engender a substitution to low toxicity pesticides and lower demand for PPE. To test for evidence of risk substitution, we estimate the causal impact of relative toxicity knowledge on WTP for gloves and masks using the following two-stage least squares specification to control possible endogenous knowledge:

$$K_{ijk}^{tox} = \gamma_0 + \gamma_1 Treat_{ij} + \sum_l \rho_l X_{li} + B_k + v_{ij} \tag{2}$$

$$WTP_{ijk} = \alpha_0 + \alpha_1 \widehat{K_{ijk}^{tox}} + \sum_l \delta_l X_{li} + B_k + u_{ij} \tag{3}$$

where K_{ij}^{tox} is the farmer's relative toxicity knowledge defined as equal to one if the farmer correctly identified the health risks of a WHO class Ib pesticide and a WHO class U pesticide[11]. In the first stage (2), we regress our excluded instrument $Treat_{ij}$, included instruments X_{li} that control for several household, farmer, tomato production, and health risk characteristics that might affect WTP, and block fixed effects B_j on K_{ij}^{tox}. The predicted values of relative toxicity knowledge $\widehat{K_i^{tox}}$ are then regressed against WTP_{ij} in the second stage (3). Valid identification in (3) requires an excluded instrument that is correlated with K_{ij}^{tox} and only correlated to WTP_{ijk} through K_{ij}^{tox}. Treatment assignment $Treat_{ij}$ meets these requirements. It affects a farmer's relative toxicity knowledge and is randomly assigned and not directly correlated with WTP_{ijk}. We also test for evidence that K_{ijk}^{tox} is endogenous using a regression based Hausman specification test outlined by Wooldridge (2003, pg. 483).

C. *Results*

a. *PPE demand*

PPE ownership and use is low but within the range reported by previous research in Southern Africa. The median number of PPE items owned is only one (shown in Table A2 in the appendix). Each PPE item was available for sale in the nearby town of Mkushi, so the low ownership and use does not reflect a complete lack of access to any item. Low PPE ownership together with the use of highly hazardous pesticides imply large health risks for tomato farmers in our study. In the year prior to the baseline interview, 84% of the sample reported experiencing an acute illness symptom shortly after applying a pesticide, and the average number of symptoms experienced was 2.8 for those that experienced one. Thirty nine percent of our sample lost at least

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[11] We showed farmers a sample pesticide in each toxicity class and asked them to identify the toxicity of each. We somewhat generously code correct responses for the class Ib pesticide as either "extremely toxic" or "highly toxic" and correct responses for the class U pesticide as either "not very toxic" or "not toxic." Responses of "I don't know" to either pesticide are coded as incorrect knowledge (we include robustness checks on this decision in the Appendix Table A7).

one work day from these acute illnesses and nearly one quarter visited a health clinic for treatment of their symptoms.

The BDM mechanisms provide WTP bids for each farmer, which allow us to map demand curves using the share of farmers that bid greater than or equal to a range of prices – shown in Figure 1. We make four observations from these demand curves. First, about 20% of the bids for each item were 0 ZMW. Farmers were not limited in their bid amounts, and could bid as low as 0.5 ZMW (approximately $0.05). This observation is consistent with previous literature that shows large decreases in demand for non-durable health goods when a positive price is charged relative to when the goods or services are offered for free. Kremer and Miguel (2007) show that charging a small fee reduced adoption of a deworming treatment by 58 percentage points in Kenya. Kremer et al. (2009) show a large increase in use of a chlorine water treatment when households received the treatment for free and an insignificant effect of a 50% subsidy relative to control group. The goods in both of these examples are non-durable health inputs similar to protective gloves and masks. Masks and gloves are only likely to last a single tomato cycle if they are used regularly.

Our second observation is that the demand curve for gloves is higher than the demand curve for masks at every price. We expect this difference as gloves offer better protection from potential pesticide exposure, and, therefore, greater health benefits if used properly, particularly when mixing pesticides prior to application. Further, gloves are slightly more durable and, therefore, offer protection for a longer period of time, though both items are not likely to last more than one growing season if used regularly.

The fact that these inputs are non-durable may contribute to the observed low demand for each item relative to the market price despite the potential savings in transportation and transaction costs associated with purchasing the items at a farmer's home instead of in the market, which is our third observation. Farmers may be reluctant to invest in health goods with short-term benefits, and repeated capital investments may be unattractive[12]. Bohm et al. (1997) suggest that the market price for a commodity is a logical upper bound for BDM game bids, but we observe a large gap between market prices and bid means. Retail outlets in the nearest major market sold gloves for 20 ZMW per pair, and the observed median and mean bids for gloves were only 5 ZMW and 7.2 ZMW, respectively, while only 17 farmers (3.6% of our sample) offered bids greater than or equal to the market price. Retail outlets sold masks for 9 ZMW a piece, and the median and mean mask bids were 4 ZMW and 4.7 ZMW, respectively, while only 75 farmers (16% of our sample) bid at least the market price. This result suggests that any intervention without a subsidy needs to have large effects to increase observed market demands for PPE.

The fourth observation from Figure 1 is that demand is inelastic at low prices for both gloves and masks, but elasticity increases with price for both items[13]. Berry et al. (2015) show a very similar elasticity relationship to price in demand for water filters in Ghana. However, there is evidence of the opposite relationship as well. In reviewing the literature on water safety, Ahuja et

[12] We also acknowledge that our research was a foreign-funded project, which may have caused some farmers to bid 0 (or lower than they otherwise would have) in the hopes that they would receive the items for free (or at a discount).

[13] We estimated the price elasticity of demand for gloves and masks by using a local polynomial regression to smooth the demand curves and calculating the point elasticities between each price and a 1 ZMW decrease in price. Table A4 in the appendix shows the results.

al. (2010) state the Kremer et al. (2009) find "evidence for very elastic demand going from zero price to a low positive price and inelastic demand as price increases." Importantly, demand is highly elastic (greater than 5) near the market price for each item, suggesting that small discounts or subsidies could increase PPE demand. The demand curve shows that a 5 ZMW discount from market prices nearly triples demand for both items. Approximately 16% of farmers offered a WTP bid of 9 ZMW (the market price for masks) or greater for masks, but more than 50% of farmers offered had a WTP of 4 ZMW or greater. For gloves, only 4% had WTP greater than or equal to 20 ZMW (the market price for gloves), but 12% offered a bid of at least 15 ZMW.

b. Pesticide knowledge

Information likely impacts PPE demand only through knowledge. Thus, an important first step in our analysis is to determine the impacts of the information intervention on knowledge. We identify these effects using ITT regressions for the two main knowledge outcomes of the training (Table 2). Our metric for knowledge of PPE benefits k^{PPE} is defined as the sum of correct responses to five true/false questions about PPE health benefits and exposure, and our metric for relative toxicity knowledge is k^{tox} (defined in IV.B above).

The intervention had a strong significant effect on relative toxicity knowledge. Treatment group farmers were 25% more likely to correctly identify both the class Ib and class U pesticide and the result is significant at the 1% level (column 1). Relative toxicity knowledge is low in the absence of training as only 13% of the control group correctly identified the toxicity of both pesticides, suggesting that there is a large knowledge gap for relative toxicities. This gap is larger for the low toxicity pesticide than for the high toxicity pesticide. Only 25% of all farmers correctly stated that the class U pesticide was not toxic or of low toxicity, while 88% of all farmers correctly stated that the class Ib pesticide was extremely or highly toxic. Further, farmers appear to have relatively flat health risk perceptions for pesticides as 62% of control group farmers perceived both the class Ib and the class U pesticide to be highly or extremely toxic.

Information did not have a significant effect on knowledge of PPE benefits (column 2). The mean knowledge of PPE benefits score for the control group was 4.1 out of 5. Thus, there was little room for information to improve farmer knowledge of PPE benefits as measured by our questions. This is an unexpected result based on observations of farmer practices and conversations during semi-structured interviews; however, there is evidence in the literature that some pesticide users are knowledgeable of PPE health benefits (see for example Yuantari et al., 2015).

c. The effects of information on WTP

Table 2 presents the intention to treat effects of information on WTP for PPE. The overall effects of being assigned to the treatment group on WTP are insignificant[14] with p-values greater than 0.5. Further, we find little evidence that information had varying effects by covariates shown in Table 3. The interaction effect of treatment assignment and an indicator variable for low knowledge of PPE benefits (bottom 30% of all farmers) is insignificant for both gloves and masks

[14] As a robustness check to our WTP estimates, we analyze market PPE purchases made between the baseline and endline surveys shown in Table A5 in the appendix. PPE purchase patterns are similar for the treatment and control groups and ITT regressions of the effect of information on the decision to purchase PPE show insignificant effects for each PPE item, confirming the null effect of the intervention on WTP revealed by the BDM mechanisms.

in all specifications. Thus, information did not have a significant effect on WTP for PPE for the farmers with larger gaps in prior knowledge. We also observe insignificant heterogeneous effects of information by education and experience.

The only significant heterogeneous effect is in the number of class U pesticides applied. Information had a negative effect on glove WTP for farmers that applied more class U pesticides (the effect is negative with a p-value of 0.213 for masks). This is potentially evidence of a risk substitution effect for relative toxicity knowledge. With better knowledge of the varied health risks of pesticides, farmers using less toxic pesticides may have less to gain from using PPE. Conversely, farmers using more toxic pesticides have more to gain from using PPE, and we find weak support of this idea. The number of class Ib pesticides used shows a positive heterogeneous effect p-values of 0.142 and 0.179 for masks and gloves, respectively. We now turn our attention to a more direct test of the potential risk substitution effects through relative toxicity knowledge.

Columns 3 and 4 of Table 2 show the first and second stage estimates, respectively, of the two-stage least squares specification in equations (2) and (3). Assignment to treatment is a strong instrument for relative toxicity knowledge; the F-statistic of treatment assignment is 25.39, well above the rule-of-thumb value that F-statistics greater than ten are strong instruments. We find no evidence of a risk substitution effect in farmer demand for PPE; relative toxicity knowledge (predicted) has an insignificant effect on WTP for both masks and gloves – estimates of $\widehat{\alpha_1}$ in equation (3). However, we fail to reject the assumption of exogeneity for both the masks and gloves estimations with p-values of 0.982 and 0.444, respectively[15].

Given the lack of evidence that knowledge is endogenous, we also estimate the effect of knowledge on WTP for gloves and masks under the assumption of exogeneity as two-stage least squares estimations may be less efficient that OLS in the absence of endogeneity. To better understand the potentially competing effects of information on PPE benefits and pesticide toxicity information on demand, we include three knowledge variables in the following specification;

$$WTP_{ij} = \alpha_0 + \alpha_1 k_i^{PPE} + \alpha_2 k_i^{tox} + \alpha_3 (k_i^{PPE} * k_i^{tox}) + \sum_l \delta_l X_{li} + B_k + u_{ij} \qquad (4)$$

where k^{PPE} is knowledge of PPE health benefits as defined in section IV.C.b above, k^{tox} is relative toxicity knowledge as defined in section IV.B above, and $(k^{PPE} * k^{tox})$ is their interaction[16]. We used the same covariate controls X_{li} and block fixed effects B_k as in equation (1). Table 4 presents the average partial effects of knowledge of PPE benefits at each level of relative toxicity knowledge and vice versa.

Knowledge of PPE benefits shows an overall positive and significant relationship to WTP for gloves and masks in each specification. A one unit increase in the knowledge of PPE benefits metric corresponds to a 0.545 and 0.775 ZMW increase in WTP for masks and gloves, respectively. The relationship between knowledge of PPE benefits and WTP is larger for the

[15] Specification tests for the gloves estimations have power greater than 0.8 for the estimated effect sizes. Though mask specification tests have small effect estimates and a resulting power of less than 0.3.
[16] We lack the three strong instruments necessary to estimate the effects of these three knowledge variables with an IV approach. We also do not have a strong instrument for knowledge of PPE benefits alone as the intervention had insignificant effects on knowledge of PPE benefits.

farmers with better knowledge of relative toxicity, suggesting that greater knowledge of each component of pesticide safety is correlated to an increased WTP for masks and gloves.

Relative toxicity knowledge has insignificant overall average partial effects on WTP, yet there are significant average partial effects when knowledge of PPE benefits is low (less than 4). The effects are larger for gloves than for masks and when knowledge of PPE benefits is lower. When knowledge of PPE benefits is zero, a one unit increase in relative toxicity knowledge (i.e., a more accurate perceived toxicity difference between class U and class Ib pesticides) corresponds to a 4.2 ZMW and 4.6 ZMW lower WTP for masks and gloves, respectively: a large effect relative to the average bids of 4.5 ZMW and 6.8 ZMW for masks and gloves, respectively. The effect diminishes as knowledge of PPE benefits increases and is insignificant and close to zero when the knowledge of PPE benefits variable equals four. These results are largely robust to trimming (estimates shown in Table A11 in the appendix).

Farmers with relative toxicity knowledge scores equal to one perceive the health risks from low toxicity pesticides to be less than those of high toxicity pesticides, and are better able to choose pesticides with lower health risks. They may, therefore, have a lower expected benefit from PPE use and a lower WTP. However, we observe relatively high knowledge of PPE benefits and that result is consistent with other studies (see for example Yuantari et al., 2015). Thus, the effect of relative toxicity knowledge insignificant on average. Note that we control for important covariates including farmer education, asset ownership, tomato experience, and sex, so these results do not stem from possible correlations between knowledge and these covariates.

To summarize our findings on PPE demand; information had an overall insignificant effect on WTP for protective gloves and masks despite some significant knowledge increases from the intervention. Thus, information does not appear to be a constraint to PPE demand for our sample. Conceptually, PPE use and pesticide toxicity may be substitutes in a farmer's health production function. Thus, farmers may be substituting risk reducing inputs in their health production functions by offering lower WTP bids for protective gloves and masks if they can reduce their health risks through their choices of pesticide toxicities. We find insignificant effects of relative toxicity knowledge on WTP for PPE using instrumental variables estimations, though we fail to reject the assumption of exogenous knowledge. When we treat knowledge as exogenous, we find evidence that farmers with higher knowledge of relative toxicity but lower knowledge of PPE health benefits have a lower WTP for both masks and gloves. These results are consistent with the literature that shows mixed evidence of risk compensation. For example, Peltzman (1975) finds evidence of risk compensating driving behaviors in response to mandatory seatbelt laws, but Cohen and Einav (2003) find no evidence.

The null effect of information on WTP for protective equipment together with the evidence consistent with a risk substitution effect through relative toxicity knowledge place greater importance on the effect of information on farmer pesticide choices by toxicity class. These effects are explored in the next section.

V. Pesticide Demand

A. Eliciting farmer pesticide choices

Using revealed preference data to analyze the impacts of information on farmer demand for pesticides by toxicity class has multiple drawbacks. While all farmers in our study area had similar access to more than 10 pesticide retail outlets, farmers do not visit each outlet prior to purchasing pesticides and each outlet carries different brands and different products with variation in products carried over a single growing season. Thus, it is unlikely that farmers observe the same choice sets of pesticides. Further, they self-select into different choice sets based on what retail outlets they visit. Because a farmer's choice set may be related to unobservable farmer characteristics, we used contingent demand experiments to elicit farmer pesticide choices that allowed us to make pesticide choice sets consistent across EAs (and therefore across treatment group assignment) and orthogonal to farmer characteristics. The contingent demand experiments also allowed us to elicit farmer pesticide choices before and after our training, whereas the timing of data collection activities – during the dry season – did not guarantee that we would collect revealed pesticide demands for each farmer at both survey rounds. In addition, the experiments allowed us to focus on the main variables of interest – information, pesticide toxicity, and pesticide prices – by controlling for heterogeneity in farmer's production techniques and pesticide choice sets.

We designed the experiments to mimic the pesticide decision processes reported by tomato farmers in our semi-structured interviews and pre-testing, and we implemented experiments for the two pests for which farmers most often use WHO class Ib pesticides: nematodes and bollworms. To motivate each pesticide choice, we described a production scenario with pest pressure on a hypothetical tomato plot and showed farmers an icon array to aid comprehension of the pest level,[17] which mirrors reality where farmers typically observe a pest in their plots prior pesticide purchase. We emphasized that the stated pest pressure was the *only* pest observed on their plots to draw a farmer's focus to a specific pest and to minimize any perceived benefits from broad spectrum controls – i.e., controlling other pests beyond either bollworms or nematodes. The production scenarios held several key variables in the farmer's tomato production functions constant, including plot size and history, plant variety, season, growth stage, weed pressure, crop health, and previous pesticide use. Immediately after each production scenario, we showed farmers a pesticide choice set of several locally available pesticides[18]. Farmers could choose not to purchase any pesticide if they so desired. We deliberately chose at least one pesticide from each available toxicity class (classes Ib, II, and U) and one product for each of the most prevalent active ingredients in the market. Lastly, each covered approximately the same area when mixed and applied as recommended.

An experimental design of 16 choice scenarios for each pest was created in a way that minimized D-error subject to the design constraints using N-gene software. We created four blocks for each experiment meaning farmers responded to eight choice scenarios – four for the nematode experiment and four for the bollworm experiment. We updated the experimental design twice

[17] Garcia-Retamaro and Galesic (2010) show that icon arrays can improve comprehension of numerical information. We present a sample icon array in Figure A4 in the appendix.
[18] Appendix Table A6 shows the products and price levels that composed the various choice sets.

during data collection; in an update, the data collected to date were used to estimate models and update the priors used to generate the designs to further increase design efficiency.

B. *Empirical model*

We rely on the random treatment assignment to identity the causal effects of information on pesticide choices using two estimation methods. First, we use our unique contingent demand data to estimate choice-level ITT first-difference regressions on pesticide choice toxicities. The experimental design – specifically, the fact that each farmer responded to the exact same scenarios at the baseline and endline, and therefore the prices and pest pressures are the same for each farmer in each choice set at both interviews – allows us to compare pesticide toxicities for individual choice occasions. We assign a simple toxicity score to each pesticide choice defined as equal to one if the farmer's choice is a class U pesticide (least toxic), three if the farmer's choice is a class II pesticide (moderately toxic), and 4 if the farmer's choice is a class Ib pesticide (highly toxic)[19]. This allows us to estimate the following first difference regression with cluster robust standard errors at the enumeration area level by linear projection model (LPM) and ordered probit (OP):

$$\Delta Tox_{ijc} = \beta_0 + \beta_1\, Treat_i + B_j + \varepsilon_{ic} \tag{5}$$

where ΔTox_{ijc} is the change in toxicity score from baseline to endline for farmer *i* in block j choice occasion *c* and $Treat_i$ is an indicator variable for random assignment into treatment group. B_j is a block j fixed effect (fixed effects excluded from ordered probit estimation to avoid the incidental parameters problem). A benefit to the first-differenced specification over a difference-in-difference specification is that any time invariant variables drop from the model including unobservable farmer level characteristics. LPM estimation of (5) shows how the exogenous assignment to receive information impacts choice toxicity changes, and OP estimation of (5) allows us to estimate the treatment assignment effects on probabilities of changing choices from one toxicity class to another.

The second estimation strategy is to estimate conditional logit regressions based on a simple random utility model that compare treatment and control group choices at the baseline and endline. The conditional logit estimations also test the impacts of information on the price effect in a farmer's choices. As outside researchers, we are unable to observe all the information farmers use in making their choices, so we assume that each individual's utility from pesticide A (denoted U_A) can be split into a deterministic component V_A derived from observable information and a stochastic component ε_A which is unobservable: $U_A = V_A + \varepsilon_A$. The stochastic ε_A allows us to estimate the probabilities that each option will be selected. We assume $\varepsilon_A$to be i.i.d. type 1 extreme value distribution (the usual assumption), and we can reduce the probabilities to a form estimated using a conditional logit with the following specification for pesticide A:

$$V_A = \beta_1 p_A + \beta_2[Treat * p_A] + \beta_3 ASC_A + \beta_4[Treat * ASC_A] + \varepsilon_A \tag{6}$$

[19] There were no WHO class III pesticides in either choice set so there is no Tox_{ict} value equal to two. As a robustness check we estimate the same regressions with class II coded as two, and class Ib coded as three. The results are not sensitive to the variable definition.

where V_A is indirect utility, and p_A is the pesticide's price. ASC_A is an alternative-specific constant (ASC) for pesticide A. Packed in the ASC is the impact of product specific pesticide attributes other than price – e.g., brand, active ingredient, and toxicity (our focus). Because we randomly assigned farmers to receive toxicity information, we expect any effect on pesticide choices from other attributes to be balanced across treatment and control groups. We estimate (6) separately for each survey round (baseline, endline) and for each experiment (bollworms, nematodes). The estimator $\hat{\beta}_2$ will test differences across treatment assignment in the effect of price on choice probability across, and the estimator $\hat{\beta}_4$ will test differences across treatment assignment in choice probabilities by toxicity classes.

C. Results

a. The effect of information on pesticide choices

Table 5 presents estimates of equation (5). The LPM estimates show negative and significant (at the 5% level) overall ITT effects on changes in choice toxicity. The treatment group was approximately 30 percentage points more likely to have decrease in choice toxicity for both experiments – approximately three to four times more likely to substitute a high toxicity pesticide for a low toxicity pesticide. Thus, information led farmers to select less toxic pesticides. The OP estimates show that the treatment group was between 1 and 4 percentage points more likely to have a negative toxicity change value and between 1 and 3 percentage points less likely to have a positive toxicity change value for both experiments (all results significant at the 5% level). This suggests a general movement away from higher toxicity pesticides towards low toxicity pesticides for the treatment group in both experiments[20]. This applies to choice changes from a class Ib to a class U, from a class Ib to a class II, and from a class II to a class U. Farmers that received information likely had a more accurate perceived ordering of pesticide toxicity health risks and perceived larger toxicity differences across each toxicity class.

The conditional logit results presented in Table 6 also show a shift towards class U pesticides for the treatment group after the information intervention. At the baseline, there are no significant differences in choice probabilities between the treatment and control groups. However, at the endline – and after the information intervention – we see large and significant differences in choice probabilities. Treatment group farmers were 16 and 13 percentage points more likely to select the class U pesticide for the bollworm and nematode experiments, respectively (both significant at the 5% level). For the nematode experiment, treatment group farmers were 17 percentage points less likely to select the class Ib pesticide (significant at the 1% level). These results are consistent with the choice-level toxicity difference regressions, and the full sample results are similar.

Table 6 shows interesting impacts of information on the price effects. The control group estimates are of $\hat{\beta}_1$ in equation (6) and the treatment group estimates are of $\hat{\beta}_2$. Price has a positive and significant relationship to choice probability for the bollworm experiment at baseline, confirming our observation that many farmers perceived higher priced pesticides to be more effective at controlling pests. The baseline results for the bollworm experiment show a large and

[20] The full sample estimates are similar, but show slightly larger effects with greater statistical significance across the table.

significant (at 1%) positive price relationship[21], while the nematode experiment shows a smaller and insignificant positive price relationship (although when estimated without the price-treatment interaction, the price coefficient is positive and significantly different than zero).

The endline price estimates show large and significant differences between treatment and control groups for both samples and for each experiment. The control group has positive endline price coefficients of 0.013 and 0.053 for the nematode and bollworm experiments, respectively, but the treatment group has negative and significantly different price coefficients. The endline price coefficient for the treatment group in the nematode experiment is -0.029, while the same estimate for the bollworms experiment is -0.097 (both estimates significant at 5%).

These results suggest that information against a price-efficacy relationship corrected the misperception that higher priced pesticides are more effective. Farmers in the treatment group were less likely to choose higher price pesticides after the information intervention, but control group farmers demonstrated a positive relationship between price and choice probability at both survey rounds.

D. Revealed demand results

As a robustness check for the contingent demand experiment results, we compare revealed pesticide demands by toxicity class across survey rounds and across group assignment. The comparisons across survey rounds are imperfect, but we make two data restrictions to make them more comparable. First, we limit our analysis to the subset of farmers that made pesticide purchases between the baseline and endline interviews. Second, we restrict the baseline purchase data to those pesticides applied on plots where tomatoes were transplanted between July and October to more closely match the timeframe of the endline data. This will help control for seasonal heterogeneity in the types of pests present on plots and the pesticide products available for purchase.

Table 7 compares toxicity market shares of pesticide purchases for nematicides and bollworm controlling pesticides by treatment assignment and by survey round[22]. Consistent with our contingent demand experiments, we see larger increases in market shares for class U pesticides for the treatment group than for the control group for both pesticide types. The treatment group purchased 3 class U nematicides at the endline compared to 0 at the baseline, and 8 class U bollworm pesticides at the endline compared to just 2 at the baseline. In contrast, the control group farmers purchased 5 class U insecticides and 0 class U nematicides at the baseline, and 0 of each at the endline.

The revealed demand market shares for class U pesticides are lower than the stated choice shares in each experiment, though we argue that this is likely to be evidence of heterogeneity in the pesticide choice sets farmers face when making their revealed choices. We do not know a farmer's choice set when making revealed demand purchases, and the class U bollworm pesticide and the class U nematicide used in the contingent demand scenarios were each relatively new (available for less than one year prior to baseline) and each was available at only one agricultural

[21] For the untrimmed sample (Table A13 in the appendix), the baseline estimate shows the price effect to be statistically different for the control and treatment group (shown in the price-treatment interaction term).
[22] A comparable table for contingent demand choice shares can be found in Table A8 in the appendix.

input dealer. Thus, it is likely that many farmers did not see these class U options when making revealed choices. The revealed demand results highlight the importance of having class U pesticides available in the market choice set to see demand shifts.

The bollworm pesticide distributions for treatment and control groups are not significantly different at the baseline, but are significantly different at the endline. The nematicide distributions differences are insignificant at the endline, but we note that only two nematicides were purchased by the relevant subset of treatment group farmers at the baseline.

Interestingly, we observe a large increase in the total number of nematicides purchased at the endline survey for the treatment group, but not the control group. Our training likely increased farmer awareness of nematode risks and made farmers more familiar with products designed to control them. The increase in nematicide use has important benefits for tomato production and may increase farmer profits. Additionally, reducing the perceived health risks for class U pesticides may encourage farmers to increase use, which may also lead to higher tomato production and increased profits.

VI. Conclusion

A wide body of literature shows that changes in health and safety knowledge can shift demand and behaviors. After receiving new risk information, consumers change behaviors relating to automobile safety, food demand, and safe sex, while producers shift activities related to mining and fertilizer application. However, the literature shows small or null effects of information in some contexts. One area where health risk information has been given considerable attention is pesticide safety, particularly in developing countries where pesticide use is increasing and more widespread than previously believed. Previous research has documented the large health risks faced by farmers in developing countries through use of highly toxic pesticides and little PPE. The literature also shows that farmers have generally low knowledge of how to avoid pesticide health risks, and, thus, concludes that farmers need better information to improve their pesticide safety behaviors.

This paper explores the effects of information on demand for the two main risk mitigating behaviors available to rural farmers: (i) using less toxic pesticides and (ii) limiting exposure to those pesticides with PPE. We use a block randomized control trial in a population tomato farmers to test these effects. To assess demand for PPE, we use two BDM mechanisms and estimate the intention to treat effects of information on WTP for PPE. To measure changes in pesticide choice toxicity from new information, we use two pesticide choice experiments with variation in pesticide toxicity among the alternatives available for selection and estimate choice toxicity change differences between the treatment and control groups from baseline (before information was delivered) to endline (after information was delivered).

We find that information had an insignificant effect on knowledge of PPE health benefits, likely due to high prior knowledge before information was disseminated. However, information did significantly improve farmer knowledge of pesticide toxicity, as treatment group farmers were XX times more likely to correctly identify the class U pesticide as being low toxicity. We also find that information did not significantly change farmer demand for PPE. Thus, information is unlikely to be a constraint to PPE adoption. However, we find interesting heterogeneous effects of information based on baseline pesticide use. Farmers that used more low toxicity (class U) pesticides stated significantly lower WTP after receiving information, while farmers that used more high toxicity (class Ib) pesticides offered significantly higher WTP bids after receiving information. The former result could be evidence of a risk-substitution effect whereby farmers that learn that their health risks are lower than they previously believed compensate by demanding lower levels of protection. These risk-substitution effects are also found in exogenous estimates of the effect of knowledge on WTP for PPE. For farmers with low knowledge of PPE health benefits, an increase in relative toxicity knowledge led to a significant decrease in WTP for PPE.

Unlike PPE demand, information did have large and significant effects on pesticide choice toxicity. After receiving information, the treatment group farmers were three to four times more likely to select a less toxic pesticide than the control group. These results are consistent across LPM first-difference regressions, conditional logit estimations, and choice share observations as well as observed demands for pesticides. Thus, information on relative toxicity knowledge led to product substitution from high risk pesticides to lower risk pesticides. Our results suggest that pesticide safety interventions should focus on information relating to pesticide toxicity rather than PPE health benefits, and they show that, when it comes to pesticide safety, what farmers do not know can hurt them through a lower demand for less toxic pesticides.

TABLES

Table 1. The effects of information on knowledge of relative toxicity and PPE benefits

Dependent Variable	Relative toxicity knowledge (0,1)	knowledge of PPE benefits (0-5)
Variables	(1)	(2)
Treatment assignment	0.248***	0.068
	(0.058)	(0.184)
Control group mean knowledge	0.13	4.06
Observations	413	413
R-squared	0.212	0.138

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 2. Effects of information on WTP for gloves and masks

Model	Linear projection model		Two-stage least squares		
			1st stage	2nd stage	
	Mask	Gloves		Mask	Gloves
Variables	(1)	(2)	(3)	(4)	(5)
Treatment assignment	0.189	0.315	0.242***		
	(0.570)	(0.767)	(0.056)		
Relative toxicity knowledge (IV)				0.78	-1.301
				(2.236)	(3.074)
Observations	413	413	413	413	413
R-squared	0.135	0.094	0.227	0.138	0.082
F-statistic			18.45		
Endogeneity test (p-value)				0.921	0.605

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. All covariates are from the baseline data. Results are robust to econometric specification: Tobit and LPM estimates show similar results. Covariate controls included in estimation, but excluded from the table.

Table 3. Heterogeneous effects of information on WTP for gloves and masks

Dependent variable	Low baseline knowledge (<median)		Completed primary school		Tomato experience		# of class Ib pesticides used		# of class U pesticides used	
	Mask	Gloves	Mask	Gloves	Mask	Gloves	Mask	Gloves	Mask	Gloves
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment assignment	0.251	-0.189	0.478	-0.079	0.307	-1.575	-0.177	-0.881	1.560	2.498
	(0.591)	(0.859)	(0.783)	(1.117)	(0.906)	(1.091)	(0.627)	(0.989)	(1.435)	(1.811)
Covariate	0.605	0.747	1.015*	0.471	0.076	0.039	-0.062	-0.082	0.275*	0.634**
	(0.633)	(1.067)	(0.509)	(1.072)	(0.074)	(0.122)	(0.388)	(0.556)	(0.155)	(0.259)
Interaction	-0.192	-0.402	-0.749	-0.609	-0.019	0.199	0.676	1.048	-0.423	-0.868**
	(0.753)	(1.291)	(0.998)	(1.447)	(0.118)	(0.159)	(0.447)	(0.760)	(0.332)	(0.417)
Observations	413	413	413	413	413	413	413	413	413	413
R-squared	0.139	0.096	0.137	0.095	0.135	0.097	0.141	0.101	0.141	0.107

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Baseline covariate controls included in estimation, but excluded from the table. Results are robust to econometric specification: Tobit and linear probability model show similar results.

Table 4. Average partial effects of knowledge on WTP for gloves and masks

Variables	Mask (1)	Gloves (2)
Average partial effects of knowledge of PPE benefits		
Overall average partial effect	0.545**	0.775**
	(0.251)	(0.302)
Relative toxicity knowledge = 0	0.268	0.502**
	(0.212)	(0.241)
Relative toxicity knowledge = 1	1.326**	1.545**
	(0.484)	(0.686)
Average partial effects of relative toxicity knowledge		
Overall average partial effect	0.142	-0.327
	(0.553)	(0.731)
knowledge of PPE benefits = 0	-4.187***	-4.595*
	(1.472)	(2.455)
knowledge of PPE benefits = 1	-3.130***	-3.553*
	(1.099)	(1.868)
knowledge of PPE benefits = 2	2.072**	-2.510*
	(0.757)	(1.313)
knowledge of PPE benefits = 3	-1.015*	-1.468*
	(0.516)	(0.855)
knowledge of PPE benefits = 4	0.042	-0.425
	(0.536)	(0.717)
knowledge of PPE benefits = 5	1.099	0.618
	(0.797)	(1.035)
Relative toxicity knowledge mean	0.262	0.262
knowledge of PPE benefits mean	4.094	4.094
Bid mean	4.489	6.833
N	413	413

Cluster robust standard errors at the EA level in parentheses. Estimates of equation (4). Covariate controls included in estimation but excluded from table. Results are robust to econometric specification; Tobit estimations show similar results. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effects of information on choice toxicity – first difference ITT estimations

Experiment	Bollworms	Nematodes
	(1)	(2)
N=413		
OLS		
	-0.283***	-0.322***
	(0.096)	(0.112)
OP - Average partial effects		
Ib to U (-3)	0.018***	0.042***
	(0.007)	(0.015)
II to U (-2)	0.048***	0.020***
	(0.018)	(0.007)
Ib to II (-1)	0.015***	0.011***
	(0.005)	(0.003)
No change (0)	-0.025***	-0.010**
	(0.009)	(0.004)
II to Ib (+1)	-0.020***	-0.016***
	(0.007)	(0.005)
U to II (+2)	-0.029**	-0.016***
	(0.011)	(0.006)
U to Ib (+3)	-0.007**	-0.031***
	(0.003)	(0.011)

Estimates are of beta 1 in equation (5). Cluster robust SEs at the EA level in parentheses. Block fixed effects included in estimation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Average partial effects of information on pesticide choice probabilities and price coefficients

	Nematodes experiment		Bollworms experiment	
	Baseline	Endline	Baseline	Endline
	(1)	(2)	(3)	(4)
N= 413				
	Average partial effects of treatment assignment on choice probabilities			
Highly toxic: Class Ib				
Alternative 1	-0.006	-0.167***	-0.012	-0.003
	(0.048)	(0.051)	(0.018)	(0.030)
Low toxicity: Class U				
Alternative 2	0.014	0.126***	0.017	0.155**
	(0.030)	(0.044)	(0.020)	(0.064)
Moderately toxic: Class II				
Alternative 3	-0.018	0.041	0.002	-0.023
	(0.0457	(0.041)	(0.019)	(0.015)
Alternative 4			0.015	-0.030
			(0.032)	(0.028)
Alternative 5			0.001	-0.082*
			(0.033)	(0.042)
Alternative 6			-0.028	-0.017
			(0.019)	(0.021)
	Price coefficients by treatment assignment			
Control	0.007	0.013*	0.119***	0.053*
	(0.013)	(0.008)	(0.029)	(0.028)
Treatment	0.004	-0.029**	-0.044	-0.097***
	(0.017)	(0.011)	(0.040)	(0.033)

Cluster robust standard errors at the EA level in parentheses. "No pesticide" selections excluded from table but not from calculations (less than 1% of choices were on pesticides). Alternative descriptions found in Table A6 in the appendix. A non-model based robustness check confirms the estimated changes in choice probabilities by toxicity class; treatment group choice shares are insignificantly different than the control group at baseline, but significantly different at endline with a large increase in class U choice shares for the treatment group.

Table 7. Revealed demand toxicity market shares by pest and by survey round

Pesticide controls:	Bollworms		Nematodes	
Survey	Baseline	Endline	Baseline	Endline
Treatment				
# of observed purchases	165	107	2	10
Class Ib	36%	32%	50%	40%
Class II	63%	61%	50%	30%
Class U	1%	7%	0%	30%
Control				
# of observed purchases	158	89	10	9
Class Ib	29%	33%	100%	67%
Class II	66%	67%	0%	33%
Class U	3%	0%	0%	0%
Pearson's Chi Square test[1]	2.84	7.22		3.38
p-value	0.248	0.031		0.189

[1] No test possible for baseline nematodes.

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APPENDICES

Figure A1. Becker-DeGroot-Marschak mechanism sample script

BDM Introduction Script

Interviewer: Please read this script in its entirety to the respondent and ensure that they understand its meaning.
You will now have the opportunity to purchase a pair of protective gloves and a dust mask. The price of each item will be determined by chance in a special game. You will not have to spend any more on any item than you truly want to. Let us begin by describing this procedure…
First, I will show you an item available for sale and ask you to tell me the MAXIMUM PRICE you are willing to pay for the Item. After you state your MAXIMUM PRICE, you will be shown a stack of cards and you will be asked to draw one. Each card lists a price. The price on the card that you draw will be the price of the item. If the price that you stated as your maximum price is GREATER than the price on the card, then you will BUY the item AT THE PRICE ON THE CARD. If the price that you stated as your maximum price is LESS than the price on the card, then you will NOT BUY the item. You CANNOT change your bid after a card is drawn. If your MAXIMUM price is Less than the price on the card you will NOT be given another chance to buy the item. You must state a price that you are actually able to pay.
We are about to begin a practice round, but do you have any questions?

SOAP SALE - PRACTICE GAME

Before we play for the Gloves and the Mask, we'll play a practice game for a bar of soap. The games for the Gloves and Mask will follow the exact same rules.
What is the MAXIMUM price you are willing to pay for this soap? (*let respondent handle the soap)*

____

Now, if you draw a card with a number that is less than or equal to (BID), you will buy the soap at the price you pick. If you pick a number greater than (BID), you will not be able to purchase the soap, even if you are willing to pay the greater number. You cannot change your bid after you draw a price card. Do you understand?
If farmer does not understand, please begin script again and allow for questions to ensure they understand.
If the farmer understands, please proceed.
Please tell me, if you pick a card with (BID + 1 kwacha) on it, what happens? *If respondent does not give correct answer, explain the rules again.*
Please tell me, if you pick a card with (BID - 1 kwacha) on it, what happens? *If respondent does not give correct answer, explain the rules again.*
So, if you draw (BID + 1 kwacha) you will NOT be able to buy the soap at that price. Do you want to change your bid?
If yes, What is the MAXIMUM price you are willing to pay for this soap? (*let respondent handle the soap)*

____

If you draw a card with price (BID), then you must be able to pay (BID). Are you able to pay (BID) now?
If NOT, What is the MAXIMUM price you are willing AND ABLE to pay for this soap? (*let respondent handle the soap)* ________________
Could you please fetch the (BID) amount and show it to me?
Now you will select a price card that will determine whether you buy the soap or not. Are you ready? *Mix cards and display them face down so respondent cannot see them.*
PLEASE DRAW A CARD.
Enumerator- please record the price on the card drawn.
Is the price on the card LESS than the Maximum bid?
If YES, Do you wish you had bid less and reduced your chances of buying the soap?
If NO, Do you wish you had bid HIGHER to increase your chances of buying the soap?
If Card Price < Bid, then complete the transaction – accept payment and give the soap.
If not, explain the outcome and why they did not buy the soap.
Do you have any questions about the game?

Figure A2. Pesticide training summary letter (page 1)

PESTICIDE SAFETY SUMMARY SHEET

NOT ALL PESTICIDES ARE VERY POISONOUS.

Some pesticides are SAFE (Green label) while others are very DANGEROUS (Red label).

Pesticide health risk information is found on the **colour band** at the bottom of pesticide packaging.

Phoskill is Red label meaning it is **EXTREMELY DANGEROUS**.

PESTICIDE HEALTH RISK COLOUR CODES:

RED	YELLOW	BLUE	GREEN
Extremely Dangerous	**Highly Dangerous**	**Moderately Dangerous**	**Slightly Dangerous**

Do you know anyone that has been sick after using pesticides?
Getting dangerous pesticides on your skin can make you sick quickly – including dizziness, headache, coughing, sneezing, nausea, diarrhea, and other symptoms.
Some pesticides have been shown to have LONG TERM health risks:
including Cancer, uncontrollable shaking, and chronic coughing.

YOU CAN CONTROL your pesticide illnesses

1) BUY LOWER TOXICITY PESTICIDES

Look at the colour label before buying pesticides.

Avoid RED label pesticides whenever possible.

Go for GREEN label pesticides.

2) WEAR PROTECTIVE CLOTHING

Use GLOVES when mixing pesticides.

Wear a MASK when spraying.

Using pesticides "Carefully" is NEVER enough to protect yourself.

HOW TO BUY PESTICIDES:

1) **What pests does the pesticide control?** Read the pesticide label first and foremost. Buy pesticides to control specific pests in your plots, but also consider additional pest controls.
2) **What is the toxicity level?** Look at the colour label. GREEN pesticides are safer.
   What is the PRICE? Price is always important, but price alone is NEVER enough to base your pesticide decisions on. A higher price DOES NOT MEAN higher quality.

Figure A2 (continued). Pesticide training summary letter (page 2)

BOLLWORM AND NEMATODE CONTROL SUMMARY

Do you recognize this tomato pest?
This is a BOLLWORM.
BOLLWORMS eat tomato fruits and can quickly ruin a tomato plot and eat through your money and effort.

Here are some products that can **control Bollworms** and other tomato pests – remember that the colour labels show how harmful the pesticide is to humans.

1) "**Benefit**" (Bifenthrin & Imidacloprid, GREEN label)
    a. Benefit also controls White flies.
2) "**Profenofos**" (profenofos, YELLOW label)
    a. Profenofos also controls Red Spider Mite, White flies, Aphids, and Cut Worm
3) "**Phoskill**" (monocrotophos, RED label)
    a. Phoskill also controls Red Spider Mite, White flies, Aphids, Cut worm, Thrips
4) "**Bollpack**" (Lambda cyhalothrin, YELLOW label)
    a. Bollpack also controls Aphids, and Thrips.

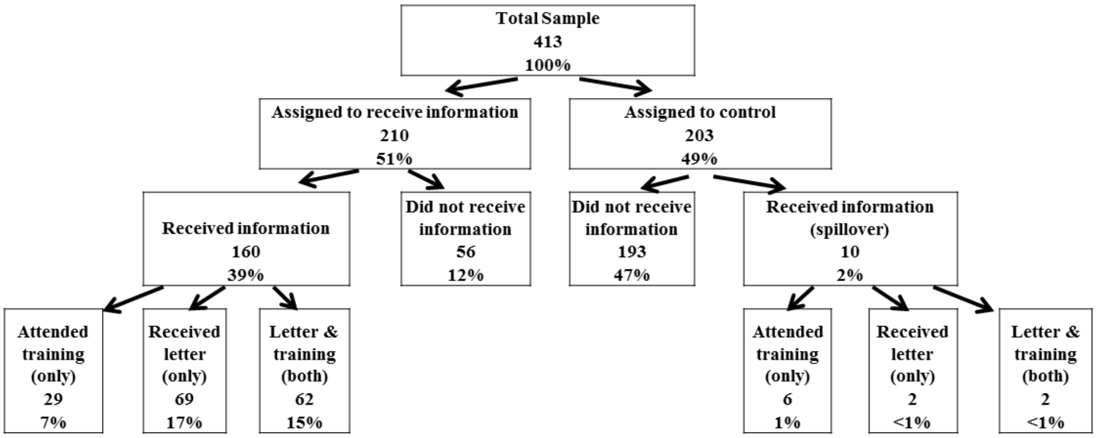
What has damaged these tomato roots?
This is NEMATODE damage.
NEMATODES are small worms that live in the soil and attack tomato roots. They reduce yields and make tomatoes more vulnerable to diseases.

Because nematodes attack tomato roots, many farmers do not even know they are affecting their tomatoes. But they can SERIOUSLY reduce tomato yields and quality and cost farmers a lot of money.

It is best to prevent nematodes by applying a pesticide when transplanting tomatoes in your plot. Ashes do **NOT** prevent nematodes. Here are a few products that can **control Nematodes -** remember that the colour labels show how harmful the pesticide is to humans.

1) "**Bio-nematon**" – (biological fungi, GREEN label)
2) "**Orizon**" – (Acetamiprid & Abamectin, YELLOW label)
3) "**Umet**" – (Phorate, RED label)

Figure A3. Experimental design and information compliance



Percentages are of the total sample.

Figure A4. Sample icon array used in contingent demand experiments

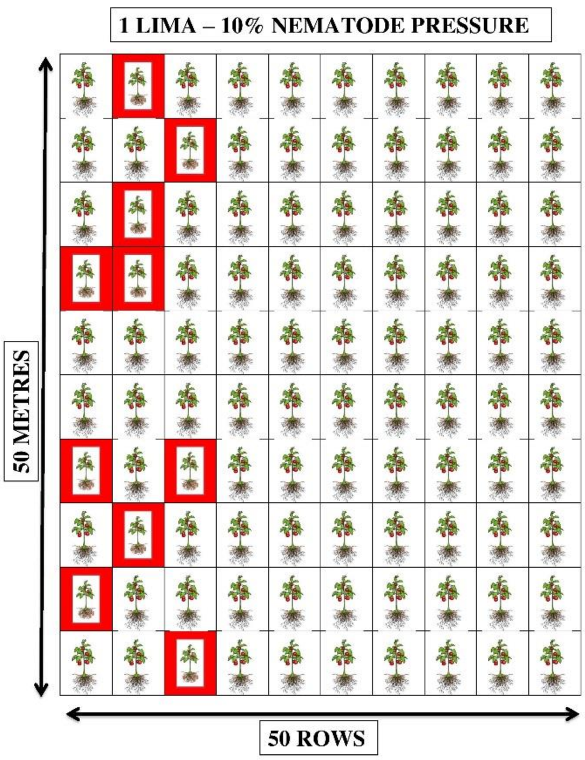


Table A1. Sample balance tests for full and trimmed samples

	Full Sample				Trimmed Sample			
Variable	Mean	Std dev	Diff	p-value	Mean	Std dev	Diff	p-value
Observations	N= 483				N=413			
Another hh member managed their own tomato plot	0.362	0.481	0.007	(0.914)	0.380	0.486	0.002	(0.983)
# of hh members age<15	2.694	1.920	-0.013	(0.960)	2.717	1.936	-0.005	(0.987)
# of hh members age>=15	3.006	1.406	0.103	(0.532)	3.044	1.381	0.037	(0.842)
Asset ownership 1st principle component	-0.147	1.713	-0.198	(0.423)	-0.061	1.749	-0.205	(0.450)
Formal agricultural training	0.083	0.276	-0.028	(0.507)	0.085	0.279	-0.008	(0.861)
Farmer age	39.000	12.466	0.938	(0.363)	39.109	12.418	1.667	(0.122)
Farmer completed grade 7	0.381	0.486	-0.08	(0.178)	0.390	0.488	-0.067	(0.319)
Farmer female	0.172	0.378	0.031	(0.530)	0.172	0.378	0.047	(0.388)
Tomato experience (# of years in last 10)	6.404	3.014	0.022	(0.945)	6.361	3.023	-0.104	(0.757)
Farmer had business income	0.516	0.500	-0.172**	(0.029)	0.511	0.500	-0.109	(0.163)
Farmer had salary/wage income	0.350	0.477	-0.009	(0.870)	0.349	0.477	-0.041	(0.480)
# of horticultural advice sources	2.986	1.358	0.452*	(0.063)	3.022	1.370	0.44	(0.111)
Total tomato area planted (ha)	0.277	0.211	0.01	(0.768)	0.274	0.209	0.038	(0.260)
Active tomato plot	0.532	0.499	0.026	(0.842)	0.516	0.500	-0.071	(0.610)
Farmer always mixes and applies pesticides themselves	0.555	0.497	0.046	(0.506)	0.552	0.498	0.039	(0.612)
Farmer owns a mask	1.876	0.330	0.021	(0.661)	1.867	0.340	0.029	(0.584)
Farmer owns gloves	1.820	0.385	0.044	(0.373)	1.816	0.388	0.064	(0.197)
# of class Ib pesticides applied	0.545	0.696	-0.041	(0.727)	0.554	0.697	-0.014	(0.916)
# of class U pesticides applied	3.296	1.311	0.035	(0.826)	3.230	1.336	-0.003	(0.985)
# of times farmer visited a clinic to treat pesticide illness	0.420	0.944	-0.061	(0.620)	0.458	0.986	-0.04	(0.775)
# of acute pesticide symptoms reported	2.358	1.824	-0.258	(0.294)	2.339	1.821	-0.128	(0.611)

Table A2. PPE ownership for tomato farmers in Mkushi, Zambia at the baseline

PPE item	Share of farmers that… Own the item	Always use the item
Full PPE (all items below)	1%	1%
Gloves	18%	11%
Dust mask	13%	6%
Boots	69%	34%
Worksuit	37%	15%
Goggles	10%	3%
Median number of items	1	0
Mean number of items	1.5	0.7

We define PPE "use" as farmers reporting that they "always use" an item, though the majority of farmers either always use or never use a PPE item; for each item, less than 7% of the sample reported occasional use. This suggests that farmers are not varying their PPE use decisions with other health risk factors like weather at application time, pesticide toxicity, and pesticide type.

Table A3. Effects of information on WTP for gloves and masks - Linear probability and Tobit models

Model	Linear probability model		Tobit	
	Mask	Gloves	Mask	Gloves
Variables	(1)	(2)	(1)	(2)
Treatment assignment	-0.053	-0.042	0.027	-0.499
	(0.055)	(0.052)	(0.699)	(0.931)
Observations	413	413	413	413
R-squared	0.186	0.181		

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. All covariates are from the baseline data. Covariate controls included in estimation, but excluded from the table. Tobit estimates shown are marginal effects.

Table A4. Price elasticity of demand estimates by price (N= 413)

	Elasticity	
Price	Mask	Gloves
1	0.19	0.09
5	1.70	0.79
10	5.12	2.48
15	11.33	4.65
20		5.30

Table A5. Endline PPE purchases by treatment assignment

	All		Treatment		Control	
PPE item	# of farmers that purchased	Share of farmers that purchased	# of farmers that purchased	Share of farmers that purchased	# of farmers that purchased	Share of farmers that purchased
Gloves	18	0.04	8	0.03	10	0.04
Mask	14	0.03	6	0.03	8	0.03
Boots	78	0.16	35	0.15	43	0.18
Goggles	10	0.02	3	0.01	7	0.03
Coveralls	16	0.03	6	0.03	10	0.04
Any PPE item	98	0.21	47	0.20	51	0.21
Mean # of PPE items purchased		0.29		0.25		0.32

Lead-farmers excluded because they were given PPE items as demonstration tools for their trainings. Farmers that reported paying a zero price for the items are also excluded.

Table A6. Pesticide products and prices used in contingent demand experiment choice sets

	Nematode experiment				Bollworm experiment			
Option numbers by toxicity class[1]	Pesticide Trade Name	Active Ingredients	Initial Price Levels[2]	Expanded Price Levels[2]	Pesticide Trade Name	Active Ingredients	Initial Price Levels[2]	Expanded Price Levels[2]
Highly toxic: Class Ib								
Alternative 1	Umet	Phorate	70, 75, 80	60, 75, 90	Phoskill	Monocrotophos	10, 12, 14	7, 12, 17
Low toxicity: Class U								
Alternative 2	Bio-Nematon	Bacteria	76, 84, 91	66, 84, 101	Benefit	Bifenthrin & imidacloprid	10, 12, 14	7, 12, 17
Moderately toxic: Class II								
Alternative 3	Orizon	Acetamiprid & Abamectin	84, 93, 102	74, 93, 112	Profenofos	Profenofos	Phoskill Price + (0, 1, 2)	Phoskill Price + (0, 2, 5)
Alternative 4					Bollpack	Lambda-cyhalothrin	8, 10, 13	6, 10, 15
Alternative 5					Blast	Lambda-cyhalothrin & imidacloprid	Bollpack price + (4. 5, 6)	Bollpack price + (2. 5, 8)
Alternative 6					AlphaGold	Alphacypermethrin	9, 11, 13	6, 11, 16

[1] Option numbers used to identify products in Table 6. [2] Prices are in Zambian kwacha (ZMW).

Table A7. First-difference effects of treatment assignment on choice toxicity OLS and OP estimates for both experiments - Revised toxicity change codes

	Untrimmed Sample		Trimmed Sample	
Experiment	Nematodes	Bollworms	Nematodes	Bollworms
OLS				
	-0.258**	-0.148*	-0.197*	-0.127
	(0.105)	(0.082)	(0.114)	(.082)
OP - Marginal effects				
Ib to U (-2)	0.055**	0.017	0.041*	0.015
	(0.024)	(0.011)	(0.025)	(0.011)
II to U or Ib to II (-1)	0.036***	0.054*	0.029*	0.048
	(0.013)	(0.030)	(0.016)	(0.032)
No change (0)	-0.013*	-0.021	-0.010	-0.020
	(0.008)	(0.015)	(0.008)	(0.015)
U to II or II to Ib (+1)	-0.039**	-0.044*	-0.031*	-0.038
	(0.016)	(0.023)	(0.018)	(0.023)
U to Ib (+2)	-0.038***	-0.007*	-0.029*	-0.005
	(0.014)	(0.004)	(0.016)	(0.003)

Cluster robust SEs at the EA level in parentheses. Choice toxicity coded as 1= class U, 2 = class II, 3 = class Ib, and differences are baseline toxicity code minus endline toxicity code. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Stated choice toxicity market shares by treatment and control group assignment

Experiment	Bollworms		Nematodes	
Survey	Baseline	Endline	Baseline	Endline
Treatment				
Class Ib	16%	12%	39%	30%
Class II	70%	55%	33%	28%
Class U	13%	33%	27%	42%
Control				
Class Ib	18%	12%	41%	39%
Class II	71%	71%	33%	31%
Class U	12%	18%	26%	30%
Chi Square[1]	1.34	63.15	0.27	31.88
p-value	0.511	p<0.001	0.872	p<0.001
Observations	N= 425			

[1] Pearson's chi-square tests are for treatment vs. control group distributions. Fewer than ten choices (less than 1%) for each experiment were "no pesticide" so they are excluded from the table.

APPENDIX SECTION 2: UNTRIMMED SAMPLE COMPARISON TABLES

Table A9. Effects of information on WTP for gloves and masks - untrimmed sample. Comparison: Table 2

Model	Linear projection model		Two-stage least squares		
			1st stage	2nd stage	
	Mask	Gloves		Mask	Gloves
Variables	(1)	(2)	(3)	(4)	(5)
Treatment assignment	0.290	-0.798	0.258***		
	(0.526)	(0.743)	(0.050)		
Relative toxicity knowledge (IV)				1.123	-3.09
				(1.951)	(2.853)
Observations	505	505	505	505	505
R-squared	0.155	0.102	0.227	0.162	0.047
F-statistic			26.45		
Endogeneity test (p-value)				0.927	0.177

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. All covariates are from the baseline data. Covariate controls included in estimation, but excluded from the table.

Table A10. Heterogeneous effects of information on WTP for gloves and masks - untrimmed sample. Comparison: Table 3.

Dependent variable	Low baseline knowledge (<median)		Completed primary school		Tomato experience		# of class Ib pesticides used		# of class U pesticides used	
	Mask	Gloves	Mask	Gloves	Mask	Gloves	Mask	Gloves	Mask	Gloves
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment assignment	0.247	-0.897	0.549	-0.283	0.208	-1.841	-0.019	-0.884	1.248	2.071
	(0.625)	(0.920)	(0.741)	(1.005)	(0.854)	(1.185)	(0.537)	(0.854)	(1.268)	(1.728)
Covariate	0.807	0.666	1.680***	1.956*	0.041	0.047	-0.076	0.526	0.124	0.469
	(0.559)	(1.111)	(0.502)	(1.026)	(0.070)	(0.157)	(0.276)	(0.439)	(0.158)	(0.280)
Interaction	0.129	0.304	-0.657	-1.309	0.013	0.164	0.571*	0.212	-0.290	-0.869**
	(0.886)	(1.346)	(1.057)	(1.424)	(0.112)	(0.173)	(0.333)	(0.623)	(0.289)	(0.397)
Observations	505	505	505	505	505	505	505	505	505	505
R-squared	0.163	0.105	0.157	0.104	0.155	0.103	0.158	0.107	0.157	0.109

Cluster robust standard errors at the EA level in parentheses. Block fixed effects included in each regression. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Baseline covariate controls included in estimation, but excluded from the table. Results are robust to econometric specification: Tobit and linear probability model show similar results.

Table A11. Average partial effects of knowledge on WTP for gloves and masks - untrimmed sample. Comparison: Table 4

Variables	Mask (1)	Gloves (2)
Average partial effects of PPE knowledge		
Overall average partial effect	0.542**	0.838**
	(0.240)	(0.303)
Relative toxicity knowledge = 0	0.302	0.705***
	(0.197)	(0.258)
Relative toxicity knowledge = 1	1.281**	1.248
	(0.559)	(0.754)
Average partial effects of relative toxicity knowledge		
Overall average partial effect	0.575	0.137
	(0.546)	(0.774)
PPE knowledge = 0	-3.455*	-2.097
	(2.041)	(3.024)
PPE knowledge = 1	-2.476	-1.555
	(1.553)	(2.328)
PPE knowledge = 2	-1.497	-1.012
	(1.087)	(1.659)
PPE knowledge = 3	-0.518	-0.469
	(0.688)	(1.070)
PPE knowledge = 4	0.046	0.073
	(0.535)	(0.771)
PPE knowledge = 5	1.440*	0.616
	(0.787)	(1.050)
Relative toxicity knowledge mean	0.246	0.246
PPE knowledge mean	4.117	4.117
Bid mean	4.783	7.305
N	505	505

Cluster robust standard errors at the EA level in parentheses. Estimates of equation 4. Covariate controls included in estimation but excluded from table. Results are robust to econometric specification; Tobit estimations show similar results. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A12. Effects of information on choice toxicity - untrimmed sample. Comparison: Table 5

Experiment		Bollworms	Nematodes
		(1)	(2)
	N=505		
OLS			
		-0.324***	-0.407***
		(.091)	(0.100)
OP - Average partial effects			
	Ib to U (-3)	0.021***	0.057***
		(0.006)	(0.014)
	II to U (-2)	0.054***	0.024***
		(0.017)	(0.006)
	Ib to II (-1)	0.017***	0.013***
		(0.004)	(0.003)
	No change (0)	-0.026***	-0.014***
		(0.008)	(0.004)
	II to Ib (+1)	-0.023***	-0.021***
		(0.007)	(0.005)
	U to II (+2)	-0.033***	-0.020***
		(0.011)	(0.005)
	U to Ib (+3)	-0.009***	-0.039***
		(0.003)	(0.010)

Estimates are of beta 1 in equation (5). Cluster robust SEs at the EA level in parentheses. Block fixed effects included in estimation. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A13 Average partial effects of information on pesticide choice probabilities and price coefficients - untrimmed sample. Comparison: Table 6

	Nematodes experiment		Bollworms experiment	
	Baseline	Endline	Baseline	Endline
	(1)	(2)	(3)	(4)
N= 413				
	Average partial effects of treatment assignment on choice probabilities			
Highly toxic: Class Ib				
Alternative 1	0.022	-0.164***	-0.010	-0.010
	(0.044)	(0.046)	(0.017)	(0.027)
Low toxicity: Class U				
Alternative 2	0.011	0.148***	0.028	0.179***
	(0.028)	(0.040)	(0.023)	(0.059)
Moderately toxic: Class II				
Alternative 3	-0.041	0.016	0.004	-0.026
	(0.043)	(0.038)	(0.016)	(0.016)
Alternative 4			0.005	-0.046*
			(0.026)	(0.026)
Alternative 5			-0.008	-0.075*
			(0.030)	(0.039)
Alternative 6			-0.022	-0.021
			(0.016)	(0.019)
	Price coefficients by treatment assignment			
Control	0.012	0.013*	0.130***	0.052**
	(0.012)	(0.007)	(0.025)	(0.026)
Treatment	-0.003	-0.028***	-0.086**	-0.090***
	(0.015)	(0.011)	(0.038)	(0.032)

Cluster robust standard errors at the EA level in parentheses. "No pesticide" selections excluded from table but not from calculations (less than 1% of choices were on pesticides). Alternative numbers match products in Table A6. A non-model based robustness check confirms the estimated changes in choice probabilities by toxicity class; treatment group choice shares are insignificantly different than the control group at baseline, but significantly different at endline with a large increase in class U choice shares for the treatment group.