Human health and pesticide use in Sub-Saharan Africa*

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Abstract: While pesticides – such as insecticides, fungicides, and herbicides – are often promoted as inputs that increase agricultural productivity by limiting a range of pre-harvest losses, their use may have negative human health and labor productivity implications. We explore the relationship between pesticide use and the value of crop output at the plot level and a range of human health outcomes at the household level using large-scale, nationally representative panel survey data from four Sub-Saharan African countries where more than ten percent of main season cultivators use pesticides. We find that pesticide use is strongly correlated with increased value of harvest, but is also correlated with higher costs associated with human illness, including increased health expenditures and time lost from work due to sickness in the recent past. We take these results as suggestive that the findings of more targeted studies are indeed generalizable beyond their original, purposively chosen samples.

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Introduction

Modern agro-chemical inputs – like inorganic fertilizer and pesticides – potentially help farmers boost productivity significantly, particularly in regions like Sub-Saharan Africa (SSA) where modern input uptake has historically been limited and crops yields low. While many existing studies have provided a strong causal link between agro-chemicals use (particularly fertilizer) and crop yields, new panel data analysis identifies a strong causal relationship between the use of modern agricultural inputs and crop yields and, subsequently, yields and economic growth (McArthur and McCord 2014). This double-link has long been well-theorized in the agricultural development and structural transformation literature (Johnson, Hazell, Gulati 2003; Johnston and Mellor 1961; Schultz 1964). But the use of modern agro-chemical inputs may also incur risks of negatively affecting human health (e.g., Weisenburger 1993; Culliney, Pimentel, Pimentel 1992) or the surrounding environment (e.g., van der Werf 1996), thereby decreasing net growth in productivity and well-being in the short and longer run. These unintended consequences may be most true of pesticides – like insecticides, fungicides, and herbicides – and especially when using classes with the highest human toxicity levels, when over-applied, or when used without appropriate precautions and protective equipment.[1]

At least some of these conditions are found in SSA. Many studies of purposively chosen farming systems in SSA find increases in pesticide use over time but little to no use of protective clothing or equipment (Ajayi and Akinnifesi 2007; Banjo, Aina, Rije 2010; Mekonnen and Agonafir 2002; Stadlinger *et al.* 2011). In a study of four countries in SSA (Benin, Ethiopia, Ghana, Senegal), Williamson (2003) found widespread acquisition of pesticides "of dubious quality" (p. 4) in repackaged containers from unlicensed dealers. It is also well-acknowledged that some types of pesticide can be destructive to agricultural land, waterways, biodiversity, and beneficial predators (Fenner *et al.* 2013; Racke 2003; van der Werf 1996) which can indirectly contribute to the deterioration of human health and productivity.

[1] The term "pesticide" is referenced throughout to mean any substance used to control pests, of which we focus on "conventional" or "chemical" varieties (EPA 2011). This umbrella term includes herbicides (to control weeds and other unwanted vegetation), insecticides (to control unwanted insects), fungicides (to control fungi and pathogens), nematicides (to control worms), and rodenticides (to control rodents) (USDA 2014).

These potentially opposing effects of pesticide use – enhancing agricultural productivity in the short run while diminishing human health and damaging the natural resource base on which current and future productivity so heavily depends – call into question the narrow policy objective of simply promoting the increased use of these chemicals; trade-offs abound. Indeed, the agricultural productivity gains may be nullified entirely where there are major indirect costs associated with applying pesticides.

Seminal work in two rice-growing regions of the Philippines, combining data from detailed health and agricultural surveys, found that pesticide use had an overall negative effect on farmer and laborer health and that agricultural productivity suffered as a result (Antle and Pingali 1994). Others have tackled some variant of these questions in other developing regions, including Latin America (e.g., Crissman, Cole, Carpio 1994). In African contexts, similar investigations have suffered from very limited sample sizes specific to particular cropping patterns (generally cotton and rice) and in areas where pesticide use is known to be high, likely due to the limited use of these chemicals in African agriculture until recently (e.g., Ajayi and Waibel 2003; Houndekon, De Groote, Lomer 2006; Maumbe and Swinton 2003; Ngowi *et al.* 2007; Ugwu *et al.* 2015). To our knowledge, there has been no broader-scale or cross-country comparable analysis of the association between productivity, health, and pesticide use in SSA agriculture that allows us to generalize the findings from studies with small samples and limited applicability across farming systems. That is our primary contribution.

Recent descriptive evidence shows that agricultural households in six countries in SSA (Ethiopia, Malawi, Niger, Nigeria, Tanzania, and Uganda) apply pesticides far more frequently than is commonly acknowledged (Sheahan and Barrett 2014). About 16 percent of main season cultivating households in nationally representative samples across six countries use some pesticide, ranging from 3 percent in Malawi to 33 percent in Nigeria. Moreover, unlike the widespread perception that pesticide use is confined to cash crops, especially cotton, Sheahan and Barrett (2014) find pesticide use is similar across plots planted in a range of crops, including staple grains, and with geographic breadth not often acknowledged in other published studies nor by the larger policy community.

In this paper, we tap newly available, nationally representative panel data from four SSA countries (Ethiopia, Nigeria, Tanzania, Uganda) to investigate the correlations between the use of pesticides in crop agriculture and both agricultural productivity and farmer-reported health outcomes and healthcare costs. Given that SSA farmers appear to use pesticides more commonly than policymakers or researchers have recognized, and that cautionary messaging and training about the use of such chemicals and the need for protective clothing and equipment are negligible in the region, a careful empirical assessment of the prospective trade-offs at large scale seems overdue. We motivate our empirical work with a brief conceptual discussion of the complex effects of pesticides use in agriculture, wherein chemicals use can both boost harvests by reducing losses but also necessitate human health care costs and reduce labor availability due to illness associated with exposure to toxic chemicals. Farmers who fail to appreciate the possible effects of pesticides on health – or means by which one might mitigate those effects – may apply these inputs in too large of quantities or without appropriate safety precautions.

While the data we employ do not include detailed, reliable information about chemical types nor clinically verified ailments, as in more spatially focused studies, this paper is the first to link pesticide use with both its crop productivity benefits and human health costs across nationally representative data spanning multiple countries and cropping systems in SSA. Such analysis is important to guide more targeted research on this interrelationship as well as tailored policies and programs that would target not only the use of more inputs, but also the safer and more appropriate use of those inputs. Although our results cannot firmly determine causal relationships, they demonstrate a clear association of pesticide use with both increased harvest value and negative human health experiences and increased health care costs in the four countries we study. Given that prior toxicology and agronomic studies establish causal links from pesticide use to human health and crop yield outcomes in smaller, experimental studies on non-representative samples, we take the associations we find in these large-scale, nationally representative, observational data as suggestive that the findings of more targeted studies are indeed generalizable beyond their original samples. With these findings, researchers, policymakers, and practitioners can direct their attention to increasing farmer knowledge around pesticide application and storage and to changing any existing farmer behavior resulting in these negative outcomes.

1. Major mechanisms

While our analysis does not enable us to establish through which mechanisms pesticide use is associated with human health outcomes and related costs, the following two sub-sections detail the major potential avenues as a means of motivating both our conceptual framework and the empirical analysis that is our main contribution. Other pathways might exist, such as through pesticides' effects on pollinators and other beneficial insects, on livestock, etc. Our aim here is merely to illustrate the prospective tradeoffs, not to provide a comprehensive enumeration of all possible pathways.

1.1. Positive impacts of pesticides on human health

Before unpacking the ways in which pesticides can negatively influence human health, it is important to remember the many mechanisms through which they can be beneficial to health. Cooper and Dobson (2007) detail a litany of these benefits, which we summarize here. Most directly, the use of pesticides reduces the incidence of harmful pests, which can severely limit yields, contribute to both pre- and post-harvest losses, or even directly impact human health as disease-carrying vectors. This increase in yields and food availability should translate into increased incomes, decreased malnutrition, and improved human health for farming households. In particular, herbicide use reduces the drudgery associated with hand-weeding, which may increase quality of life and decrease energy expenditure as well as physical hardship and risk of injury. On SSA specifically, Gianessi and Williams (2011) argue that herbicide use remains a significantly underutilized method of increasing yields and saving labor on farm. Farmers may also benefit from a widening array of crop varieties and times of the year when agriculture is viable with pesticide use.

Indirectly, farmers benefit through revenue gains from more marketable agricultural surplus or the reduced need to buy food, both of which facilitate the purchase and consumption of nutrient-rich foods or better health-related practices (like visiting a doctor preemptively, procuring medicines, purchasing and using a mosquito net to prevent malaria, etc.). Similarly, if these pesticides are labor-saving technologies and relatively less expensive than the human time needed as a substitute, then farmers enjoy increased profits not only from increased revenues but also from reduced costs of other agricultural inputs, should all else remain constant.

Cooper and Dobson (2007) also point out that benefits may extend beyond the farming households using pesticides. Consumers benefit through increased food supply which should result in decreased food prices in areas not well integrated into national and global food markets. This may be a particularly important point in developing countries where increased access to food may mean healthier communities and more energy to engage in the labor market productively. Release of labor from manual agricultural tasks may also contribute to more vibrant and economically diverse rural areas. Further afield, controlling pests on export crops can mean the containment (geographically) of pests that could potentially cause negative effects in other countries' farming systems. In sum, the prospective gross gains from pesticide use are considerable.

1.2. Negative impacts of pesticides on human health

But with these gains comes the potential for real costs. Pesticides, depending on their class and type, are often toxic to humans, as is well documented in the toxicology literature (Hayes 1991). The World Health Organization classifies pesticides by their human toxicity level; generally speaking, insecticides and fungicides are far more toxic to humans than herbicides given their differences in chemical make-up (WHO 2009). Occupational pesticide exposure can have minor to acute negative neurological, respiratory, immunologic, and reproductive effects, and the use of certain types of pesticides is positively related to diagnoses of cancer (Weisenburger 1993). Research also shows that pesticides can damage human immune systems, increasing the incidence of short term sickness over time (Culliney, Pimentel, Pimentel 1992).

Harmful encounters with these chemicals can occur in a number of situations. Most directly, farmers or other agricultural laborers applying chemicals to crops risk contact via exposed skin and eyes, both of which can absorb chemicals at potentially toxic levels, or through ingestion via the mouth and nose. Beyond the time of application, contact with chemical residues during other agricultural tasks (like weeding, thinning, and harvesting) can also be problematic. Limiting exposure is possible by wearing protective clothing and utilizing other equipment that keeps the chemicals away from the body. The use of protective equipment appears to be very low in SSA, however (Ajayi and Akinnifesi 2007; Banjo, Aina, Rije 2010; Maumbe and Swinton 2003; Mekonnen and Agonafir 2002; Stadlinger *et al.* 2011).

Non-agricultural laborer members of a farm household with pesticide application are also likely to come into contact with these pesticides. Other household members — particularly children — are likely to walk through or play in fields with chemical treatment, especially those located near dwellings. The storage of chemicals, especially in open containers, in close proximity to where household members congregate, eat, or sleep is another way for household members to come into contact with harmful substances. Oluwole and Cheke (2009), for instance, found high prevalence of improper storage and many farmers leaving emptied containers in the field after use in Ekiti state, Nigeria. While likely of lesser salience, household members can also be exposed to chemical residues through accumulation in common dust or through consumption of food with residues.

Furthermore, rural agricultural households with limited resources often reuse pesticide containers. Where residues are not entirely cleaned from a container's internal surface and family members will ingest the contents later put into the containers (collected water, stored grains, etc.), the potential for also consuming pesticide residues is high. Williamson (2003) notes that over three-quarters of all pesticide poisoning cases reported to partners of the Pesticide Action Network in Benin and Senegal were related to food and drink contamination, not to exposure on fields.

Applied pesticides can also pollute the environment from which rural households critically depend and derive livelihoods, indirectly affecting human health. Pesticides used in high amounts or applied at inappropriate times (e.g., directly before rainfall) could contribute to chemical run-off and the contamination of drinking water for the surrounding rural population. Pesticides also tend to damage agricultural soils through the degradation of beneficial soil microorganisms and the sorption or binding of important organic or mineral components (van der Werf 1996); poor soils will inevitably lead to lower harvests. Evidence from West African countries, including Niger and Nigeria, shows pesticide dissipation into and accumulation in soils (Rosendahl *et al.* 2008). Taken together, the potential for significant costs related to pesticide use, particularly misuse and haphazard disposal, are also known to be high.

2. Conceptual framework

Given both the positive and negative expected outcomes associated with pesticide use on farm, critical questions arise around the choices farmers make about pesticide use as well as the actual outcomes of pesticide users across SSA. Several researchers have offered more formal economic models that in some way link pesticide use with human health outcomes, including Waterfield and Zilberman (2012), Antle, Cole, and Crissman (1998), Antle and Pingali (1994), Harper and Zilberman (1992), and Okello and Swinton (2010). Given that our contribution does not come from analytical modeling of the relationships we explore empirically, we offer a more compact, qualitative discussion of the decision making process farmers pursue in the presence of potential on-farm losses that might be mitigated through pesticides use.

Consider a farming household faced with an outbreak of pests, disease, fungus, insects, or weeds. In order to prevent loss on their fields, the household must decide whether to apply a pesticide and, if so, in what amount. If we assume that the farmer is making a profit- or utility-maximizing decision, then the farmer considers the expected size of the losses without pesticide application relative to what he or she might be able to salvage with the use of these chemicals. These marginal benefits will manifest in both harvested output and household income. Presumably a farmer can approximate yield levels under a no pesticide use scenario based upon past experiences, although estimates on loss abatement are less likely grounded in evidence when an input is new or when information about the benefits has only been offered by others. Moreover, even when a pesticide has been used in the past, farmers are unlikely to have experimented with a range of application amounts that would offer a distribution of responses useful in arriving at an optimal application level.

Simultaneously, the farmer considers the marginal costs of pesticide use. As with all inputs, there are acquisition costs associated with procurement at local markets or agrodealers as well as the transport costs back to farm. Farmers are inevitably very aware of those particular marginal costs.

But unlike many other modern inputs – like hybrid seeds – there are other, perhaps less obvious costs associated with the health risks of handling, storing, and using toxic chemicals. If farm laborers become sick and unable to work due to pesticide use contamination, labor availability falls and may drive up labor costs or reduce output due to labor market imperfections (Dillon and Barrett in press). Illness caused by pesticides may also increase household healthcare costs, including visits to a clinic or healthcare professional as well as any medicines or other treatments. Sickness among children in the household could also mean reduced time spent in school, which may harm the child's learning and likelihood of completing a degree, and increased time away from work for household members who serve as caregivers.

A farmer must be aware of these prospective health costs in order to compute an optimal pesticide application rate that balances the marginal output and income gains with the full set of expected health and labor costs associated with pesticide use. And because agronomic conditions, labor endowments, initial human health status, access to health care, etc. all vary, optimal application levels surely vary markedly, even within the same community, making it difficult for farmers to readily extrapolate from others' experiences to identify one's own optimal application rate. Furthermore, human health risks and costs may be less obviously attributable to pesticide use and therefore easily overlooked. The end result is a significant risk of overapplication or mishandling of pesticides.

Existing evidence from regions within several SSA countries where pesticide use is thought to be high suggests that farmers' knowledge of personal safety when applying pesticides is low (Mekonnen and Agonafir 2002; Ngowi *et al.* 2007) and also that farmers were unable to correctly order pesticides by their toxicity levels (Maumbe and Swinton 2003). On the contrary, in cotton producing areas of Côte d'Ivoire, Ajayi and Akinnifesi (2007) found that half of their purposively drawn sample of farmers understood the risks presented on pesticide labels, but that compliance with the safety suggestions was still inadequate. In short, the limited empirical evidence seems to support our motivating concern that farmers might not be aware of safe pesticides use levels or practices, or might be somehow bounded away from compliance, which in turn results in the unsafe use of chemicals or failure to employ risk mitigation strategies.

In the analysis that follows, we empirically investigate three hypotheses that follow directly from this conceptual framework: that pesticide use is associated with increased harvested crop output, increased health care expenditures, and decreased labor availability. While data limitations prohibit us from computing optimal levels of pesticide use given these potential benefits and costs then comparing those levels with actual farmer decisions, the presence of the latter two effects might suggest widespread misunderstanding of the costs of pesticide use, which might lead to overuse or misuse. Our empirical exercise describes correlations across these several relationships in an effort to provide a roadmap for future research that can pursue more targeted investigations of the causal mechanisms behind these statistical associations and identify appropriate interventions.

3. Data and variable construction

The data used are drawn from a subset of the countries in the Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA), collected by national statistical agencies in partnership with the World Bank. While cross-sectional or panel data sets currently exist in six countries (Ethiopia, Niger, Nigeria, Malawi, Tanzania, Uganda), we focus this analysis on the four where the percentage of pesticide-using households is the highest (Ethiopia, Nigeria, Tanzania, Uganda), as described in more detail by Sheahan and Barrett (2014).[2] Specifically, we utilize two waves of the

[2] Sheahan and Barrett (2014) find that of their sample of main season cultivating households, 30.5 percent use pesticides in Ethiopia (2011/12), 3.0 percent in Malawi (2010/11), 7.8 percent in Niger (2011/12), 33.0 percent in Nigeria (2010/11), 12.5 percent in Tanzania (2010/11), and 10.7 percent in Uganda (2010/11). We choose the four countries where at least ten percent of households apply one of these chemicals in the main growing season in these particular cross-sections since the absence of adequate variation in pesticides use in the other two countries makes analysis of those data essentially infeasible for our research question.

Ethiopia Socioeconomic Survey (2011/12 and 2013/14), two waves of the Nigeria General Household Survey (2010/11 and 2012/13), three waves of the Tanzania National Panel Survey (2008/09, 2010/11, and 2012/13), and three waves of the Uganda National Panel Survey (2009/10, 2010/11, and 2011/12).[3] Details on the sampling strategies and framework for each country and panel can be found in the basic information documents (BIDs) on the LSMS-ISA website (http://go.worldbank.org/BCLXW38HY0). We start with a balanced panel at the household level,[4] but then confine our sample to agricultural households cultivating in the main growing season. The focus on agricultural households within the balanced panel creates an unbalanced panel of households across time when households move in to and out of cultivation. We apply household sampling weights in all analysis, including with models specified at the plot level.[5] Table 1 provides more details on the sample used in our analysis.

In these data, we observe pesticide use at the plot level.[6] In some countries these data include all pesticide types lumped into one question, a major shortcoming, but in others we observe pesticides applied by category (e.g., pesticides, herbicides, fungicides).[7] In no case do we observe specific chemical type (e.g., DDT, endosulfan, malathion), as is more common in toxicology studies with a narrow geographic focus.[8] Moreover, continuous application rates of pesticides observed in the data (where available) are known to be a mix of diluted and concentrated volumes and weights, rendering the continuous measures incomparable even within a country or data set. Plot level pesticide use is therefore

[3] All data sets are nationally representative except for Ethiopia 2011/12 which is representative of rural areas only.
[4] In Tanzania and Uganda, we also include households that "split" from a "parent" at some point during the panel.
[5] We use the weights provided in the first wave of the survey in all countries except Nigeria where a "panel weight" is provided with the data.
[6] While we use the term "plots" throughout our text, the parcel level (synonymous with field level) was chosen in Uganda.
[7] We observe use of pesticides, herbicides, and fungicides separately in Ethiopia; pesticides and herbicides in Nigeria; then a lump sum of all pesticides in Tanzania and Uganda (alongside a categorical variable for the "most important type"). It is important to note that pesticides are not considered in these surveys an umbrella category under which more specific chemical types would fall, contrary to the definition from EPA (2011). In Ethiopia, no further details on categories were provided to enumerators; in Nigeria, pesticides are defined as "a substance destroying pests, especially insects and small animals like rats," implying both insecticides and rodenticides. When we aggregate across chemical types and use the term "pesticide," we refer back to original definition as described in footnote 1.
[8] Several of the studies with more specific detail on chemical type also finds that farmers or agricultural laborers often do not know the name of the chemicals they use (e.g., Stadlinger *et al.* 2011), suggesting that more detail would not necessarily add more value or accuracy to our analysis of farmer-reported survey data.

most reliably analyzed as a binary variable in these data; the lack of reliable, continuous measures precludes the use of these data to estimate optimal application amounts. Figures A.1-A.4 in the Appendix spatially describe the prevalence of pesticide use when aggregating across agricultural plots to the household level for one cross-section of data in each of the four sampled countries. These figures demonstrate the considerable geographic heterogeneity in pesticides use but necessarily do not depict the great variation among households within regions.

In the household modules, several questions related to health are asked about all household members. Most uniformly across countries, the basic health status of individuals is recorded. These questions are not specific to pesticide exposure or poisoning but, instead, refer to the general incidence of short term sickness (generally within the last 4 weeks) and, in some cases, longer term or chronic illness. Where exact symptoms are given, we only exclude cases that are more specific to injury (e.g., broken bones, aching back) than actual sickness.[9] In most countries, we also observe if individuals visited a health worker in the recent past or missed work or other usual activities on account of sickness. The two variables for which we can most directly establish costs associated with sickness or illness are (i) the value of all health expenditures (observed at the individual level, where available, and inclusive of medicines, tests, consultations, and patient fees and should be exclusive of preventative care) and (ii) the value of lost work time due to sickness (created by multiplying the self-reported number of days lost from work by a geographically-proximate median agricultural daily wage rate[10]).

The value of harvest at the plot level is constructed using the crop income valuation methodology from the Rural Income Generating Activities (RIGA) project housed within the Food and Agriculture Organization (FAO) of the United Nations (for details, see Covarrubias, de la O Campos, Zezza 2009).[11]

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[9] We make no effort to use any of the other symptoms or illness types provided by respondents as a way to more narrowly focus on the types of illness that are most likely to be associated with pesticide exposure or poisoning because we cannot expect individuals to accurately self-diagnose.

[10] We apply the same strategy for creating median wage rates across all countries. This process involves calculating a median where at least 10 wage observations were provided starting with the lowest level of geographic proximity, then moving through each subsequently larger administrative unit until all households have a wage value specified.

[11] For more on this project, see: http://www.fao.org/economic/riga/rural-income-generating-activities/en/

This involves valuing all harvest (regardless if it was sold, own-consumed, lost post-harvest, etc.) using producer prices assembled at different geographic levels. The RIGA methodology is standardized, allowing us more accurate comparisons across the four countries. The value method of computing output also enables us to aggregate across all crops planted and harvested on plots, as would not be the case when specifying in weight metrics, for example. We create these harvest values for all data sets apart from the first wave of Ethiopia data, for which harvest quantities by crop and plot are not available.

Descriptive statistics for our main variables in our analysis can be found in Table 2. While these multi-topic surveys are mostly comparable in their composition across countries, we include details of the content of the questions underlying the health-related variable construction for each country in Table A.1 of the Appendix. All monetary values used in our analysis are standardized to USD using official annual average exchange rates from the World Bank.[12] For all countries where the data span two years, we use the first year as the reference point.

4. Estimation methods

The following two sub-sections describe the panel data methods used to estimate the conceptual relationships that follow from the framework described in Section 3. Given the data constraints we face, our strategy makes no attempt to identify causal associations between pesticide use, crop productivity, and human health outcomes. Instead, our aim remains to uncover correlations and relationships between these variables, essentially to see if the causal statistical associations established in other, experimental studies on small, non-representative samples appear as well as correlations in larger-scale, nationally representative, and cross-nationally comparable data. Put differently, the main contribution of our study is to see if experimental findings on the agricultural productivity and human health effects of pesticide use are plausibly generalizable (i.e., externally valid) in SSA agriculture more broadly.

[12] These exchange rates can be found at http://data.worldbank.org/indicator/PA.NUS.FCRF. At the time of writing, an official value for Ethiopia in 2013 was not available. In its place, we used a rate from xe.com.

4.1. Crop productivity outcomes associated with pesticide use

To test the hypothesis that pesticide use is associated with higher harvested output and income levels, we specify a simple linear approximation to an unknown harvest value function for plot j cultivated in the main growing season t (long rainy season for Tanzania and first season for Uganda; only one cropping season recorded for Ethiopia and Nigeria) by household k located in administrative area g:

$$y_{jkgt} = \beta_0 + \beta_1 c_{jkgt} + \boldsymbol{\gamma v_{jkgt}} + \tau_t + \varphi_{gt} + \omega_{kg} + \varepsilon_{jkgt} \tag{1}$$

where y is the value of all harvest at the plot level (inclusive of all crops), c is the binary pesticide use variable, $\boldsymbol{v}$ includes all observed plot level characteristics (including crop-type controls) and other inputs that are expected to contribute to crop productivity, τ is a survey and cropping year fixed effect that captures intertemporal variation in covariate weather, price, and agronomic conditions nationwide, φ is an administrative unit fixed effect that varies by year (region for Ethiopia, state for Nigeria, region for Tanzania, district for Uganda), ω is a household fixed effect, and ε is a random error term. All standard errors are clustered at the household level. Because we can value crop output for only one cross-section of Ethiopia, we adjust our control variables and fixed effects strategies for it accordingly. We specify y in both linear and natural log terms. Our coefficient estimate $\hat{\beta}_1$ describes the crop productivity gains associated with pesticide use, the hypothesis of interest. While we take as many possible precautions against endogeneity in our set up, the pesticide use variable cannot be considered strictly exogenous, hence our focus on correlations only.[13]

This simple specification does not distinguish between pesticide use for loss abatement rather than for increased biomass production, as suggested by Lichtenberg and Zilberman (1986) or Carrasco-Tauber and Moffitt (1992). We simply aim to understand the correlation between pesticide use and harvested crop outcomes, whatever the mechanism in play prior to harvest. Furthermore, in our data, a

[13] For example, data constraints preclude our ability to add plot-specific fixed effects, implying that any unobserved differences in plot quality may bias our estimates. Where available, we control for this using farmer perceptions of soil/plot quality which we expect to be highly correlated with actual quality. An additional source of prospective endogeneity arises where pesticides are used in areas endemic to pest outbreaks. We also recognize that there may be interaction and higher order effects but choose to estimate simple models since we are merely interested in establishing a correlation.

high percentage of farmers apply pesticides to fields where they report no incidence of pests, implying the use of pesticides as a preventative (not damage control) method.

4.2. Human health outcomes and costs associated with pesticide use

To test the hypotheses in that pesticide use is associated with decreases in labor availability and increases in household expenditures on healthcare, we estimate a number of models at the household level k derived from the following simple linear form:

$$\boldsymbol{h_{kgt}} = \rho_0 + \rho_1 c_{kgt} + \theta_t + \mu_{gt} + \epsilon_{kgt} \tag{2}$$

From the set of health outcomes available in the LSMS-ISA data sets, $\boldsymbol{h}$ contains the value of health expenditures related to recent illness, the value of time lost from work due to illness, the number of days lost from work due to illness, a binary variable specifying if any time was lost from work, a binary variable indicating a household member fell sick in the recent past, a binary variable describing whether a household member recently visited a health worker due to illness, and a binary variable where a household member has a long-term or chronic illness. We choose to aggregate from individual level responses to the household level for two reasons: (i) the expected human health implications experienced by more than just laborers working on plots with pesticide application (as described in Section 2.2) and (ii) data constraints on accurately creating a full roster of household members who have worked on a given plot.[14] As such, c represents a binary variable that describes where pesticides are used on any plot within a household's farm, and h is an aggregation across household members.

Similar to model (1), θ is a survey year fixed effect that captures intertemporal variation in the incidence of illness at the national-level, μ is an administrative unit fixed effect that varies by year (which should control for spatial differences in disease burdens and in area-based chemical applications, e.g., for

[14] In Uganda, for example, respondents claim that more than three household members work on a given plot in over 50 percent of cases, however the details for only three individuals are collected due to questionnaire structure. This implies that a full roster of household members working on particular plots cannot be constructed. Additionally, experimental evidence from Tanzania show that many respondents in the LSMS-ISA surveys forgot to report individuals who worked on a plot given the long length of recall inherent in the labor modules (Arthi *et al.* 2015).

mosquito control), and ϵ is a random error term. The ideal strategy would be to also control for time-invariant household-level characteristics that may influence health outcomes independently of pesticide use via an added household fixed effects term. But, because our c and several of the variables included in $\boldsymbol{h}$ are binary variables, lack of variation over time from the perspective of a household in either or both impedes our ability to estimate our model with these fixed effects so we choose to exclude them. Our main specification includes no other household-level control variables.[15]

We use two types of estimators where our outcome variable is continuous and includes a high proportion of zero values in order to check the sensitivity of our results: Ordinary Least Squares (OLS) and a left censored-Tobit model. Like our previous model, all standard errors are clustered at the household level. Here, our estimated coefficient of interest, $\hat{\rho}_1$, describes the human health outcomes associated with pesticide use on farm. When the dependent variable is the value of health expenditures related to recent illness, coefficient estimate $\hat{\rho}_1$ serves as a test of the hypothesis that pesticide use increases the cost of health care. For the dependent variables time lost from work, falling sick in the recent past, or suffering chronic illness, $\hat{\rho}_1$ serves as a test of the hypothesis that pesticide use aggravates future labor constraints.

5. Results and discussion

In addition to our main results, as presented in Tables 3-6, we also refer to a number of robustness checks and disaggregated results that appear in the Appendix.

5.1. Crop productivity

[15] Even studies using data far more specific to the effects of interest use very few control variables and, when they are included, there is typically little to no statistical significance. For example, Pingali *et al.* (1994) include age, weight/height, and smoking and drinking behavior with very few instances of significance in these control variables when performing their regression analysis at the individual level; no other household-level socioeconomic variables are included.

Table 3 presents partial results of estimating equation (1) under several specifications (with full regression output for each country in the Appendix). In all four countries, we find that pesticide use is associated with statistically significant increases in the value of harvest on a given plot. In Ethiopia, plots with pesticides have harvest values 19-32 USD more than plots without pesticides; 68-85 more in Nigeria; 40-62 USD more in Tanzania; and 38-52 USD more in Uganda. When including the natural log-transformed version of the value of harvest as the dependent variable instead (columns 4-6), we find remarkable similarity in magnitude on the coefficient estimates on the pesticide binary variable across three of the four countries (Ethiopia, Tanzania, Uganda); in these cases, there is approximately a 33 percent increase in harvest value on plots where pesticides are used in the main growing season. This level of cross-country consistency in statistical significance and magnitude is not achieved for any of the other variable inputs included in each regression (e.g., chemical fertilizer, organic fertilizer, irrigation).

These results hold when using a full suite of controls variables, including crop-type fixed effects (except in Nigeria) which should control for any correlation between crop market values and pesticide application. Results retain most of their significance – although magnitudes do shift downward – when estimating the same models with the outcome variable standardized per hectare instead (see Table A.6 in Appendix). The sizable, consistent, positive partial correlation estimates strongly suggest agricultural productivity gains associated with pesticide use.

5.2. Human health costs

We next explore Table 4, which shows the results of various models that explore the correlation between human health costs and pesticide use, some of the outcomes of interest from equation (2). Columns 1-3 of Table 4 present the relationship between the value of health expenditures on account of illness (e.g., curative work and treatments) and pesticide use at the household level. In the three countries for which we can study this value (Nigeria, Tanzania, Uganda), all pertain to costs incurred over the last month; however, in Nigeria, these costs are only associated with the first consultation and, therefore, may underrepresent the full cost where the household incurred additional expenses beyond one visit to a health care provider (see Table A.1 in the Appendix). Throughout, we observe positive and statistically significant relationships between pesticide use and household health expenditures in all three countries, with effects of similar magnitude in Tanzania and Uganda. We perform robustness checks by replacing the Tobit estimator with simple OLS (Table A.8 of the Appendix). In Nigeria, the statistically significant coefficient estimates disappear in the OLS specifications, likely because 74 percent of household observations are zero values (relative to 28 in Tanzania and 34 in Uganda) or due to the high share of herbicide use relative to other types, which should be less toxic.

One might reasonably worry that these results merely pick up a household income effect – i.e., wealthier farming households can afford to both purchase pesticides and incur health expenses. We therefore re-estimate the specifications from Table 4 with an added total household income control variable as constructed by RIGA (see Table A.9 in Appendix). In Uganda and Tanzania, the coefficient estimates on the pesticide variable keep their sign and significance throughout; income variables are positive and statistically significant as well. In Nigeria, on the other hand, the significant effects disappear, and the income variables are not statistically significant either. In sum, the results displayed in Table 4 are independent of farmer income levels in the two countries for which we observe reasonable variation in household health expenditure levels.

Columns 4-6 of Table 4 display the results related to our other value measure: the value of time lost from work due to illness. The descriptive statistics (Table 2) indicate that these values are always larger (on average across the sample in each cross-section) than the aforementioned health expenditures. In Ethiopia, the coefficient estimates are only positive and statistically significant (at the 10 percent level) in the regressions with most controls. In Nigeria, statistically significant coefficient estimates emerge in only one specification. In Uganda, we observe three specifications with positive and statistically significant coefficient estimates. Because differences in local wage levels may abstract from these value-specific associations – and more specifically because spatial variation in wage levels may correlate independently with pesticide use – we also present the raw number of days lost from work in Table A.7 of the Appendix. Mostly similar relationships emerge, but with increased significance in Nigeria and

Uganda and decreased significance in Ethiopia. Some of these differences across countries may be on account of slightly different recall periods in the underlying questions asked of respondents: one month in Nigeria and Uganda while two months in Ethiopia (Table A.1 in the Appendix).

Columns 7-9 of Table 4 show the combined measurable human health costs (from healthcare expenses and the opportunity cost of lost labor time) for the two countries with both of these measures, Nigeria and Uganda. By adding these values together, this outcome variable very nearly resembles similar measures in studies with more appropriate data sets but small samples, including Houndekon, De Groote, Lomer (2006). Here we find positive and highly statistically significant results for Uganda, but no statistical significance for Nigeria. In Nigeria, the value of reported time lost from work is more than four times greater than the value of health expenditures related to illness, as opposed to a near match in Uganda, implying that the separately insignificant effects on the value of time lost wash out the the value of health expenditures in this combined outcome variable.

One important extension of our main analysis breaks the pesticide aggregate variable into its constituent types where we can, in Ethiopia and Nigeria. We re-run the last two specifications specific to the types of pesticides used – herbicides versus non-herbicides (all bundled) – given the differences in toxicity to humans (see Table A.10 of the Appendix, see Table A.11 of the Appendix for results with added income control). In most cases, we find that herbicide use accounts for the positive and statistically significant estimated relationships, especially in Ethiopia. This finding complements related work on the "herbicide revolution" occurring in some SSA countries. In Ethiopia, for instance, Minten *et al.* (2016) note a major increase in herbicide use among teff growers, from around 30 percent applying ten years ago to over 60 percent now. In Nigeria, herbicides and non-herbicides appears to contribute equally to higher health expenditures where the value of health expenditures from sickness is the outcome variable.

Recall from Table 2 that herbicide use constitutes the bulk of reported pesticide application in both Ethiopia and Nigeria. But also recall that herbicides are typically *less* toxic to humans than are insecticides and fungicides. These results are concerning and suggest the need for follow on analysis with more appropriate data to understand exactly what types of pesticides farmers are using and how they use them. Without the ability to investigate further with the data on hand, we offer three possible reasons for these anomalous results.

One – in Ethiopia especially – is that households are unable to discern between chemical types and, therefore, incorrectly identify the chemical types they use on farm during data collection. That is, the problem is measurement error.

A second potential reason is that the types of herbicides used in Ethiopia (and perhaps elsewhere) really do have toxicity levels harmful to humans; chemicals banned or replaced in high-income countries are often sold and used in SSA. For example, both Dichlorophenoxyacetic acid (commonly known as 2,4-D) and trifluralin are used in Ethiopia;[16] these compounds are 10 and 140 times more toxic for humans than glyphosate, the most commonly used herbicide in the United States, which replaced these more toxic herbicides (Fernandez-Cornejo *et al.* 2013).

A third potential reason arises from the timing of data collection on short term health effects relative to herbicide application. It may be the case, for example, that the acute toxicity effects of insecticide and other more harmful pesticide use had dissipated by the time the household was surveyed, and therefore the data reflect inflammations of chronic effects rather than acute toxicity that would be captured in data collected more immediately after chemicals application.

A simple tabulation of the crops to which herbicides are applied reveals that teff and wheat are the main recipients in Ethiopia. In Nigeria, we observe pesticide use at the plot level and note that herbicides are used with highest frequency on plots where the farmer-identified "main crop" is maize or rice. This further motivates analysis of how the overall human health effects we uncover pertain to staple crop producers, the bulk of SSA's smallholder farmers, who have typically been excluded from literature on this topic. Because we observe all crops planted on each plot, we are able to perform our analysis on a

[16] See, for example, http://addisfortune.net/articles/first-herbicide-factory-to-begin-production-with-27m-br-investment/ on 2, 4-D use and Grichar *et al.* (2011) and Sahle and Potting (2013) on use of trifluralin in floriculture, sesame and wheat production.

sub-sample of households that produce staples.[17] Here, we redefine our main variable of interest as having applied any amount of pesticide to at least one plot containing staple crops. Then, we drop from our sample any households that applied pesticides to plots with cotton or rice, crops typically studied in this context, to ensure that we do not pick up the effects related to the application of both cotton or rice *and* staple crops. These results can be found in Table A.12 of the Appendix. Across nearly all outcome variables and specifications, our results retain their sign and significance; in some cases, significance increases, particularly for Ethiopia with respect to the value of lost days from work. These findings clearly demonstrate that the negative association between human health and pesticide use is not narrowly restricted to the small set of crops that have been studied to date. Indeed, pesticide use on staple food crops is also correlated with costly health outcomes across all countries under study.

Together, these results suggest that pesticides-using households are indeed more likely than those that do not use pesticides to lose some work time and potential income as a result of illness. Of course, this could be interpreted as beneficial rather than problematic if pesticides are labor-saving and used in response to shortages caused by illness rather than causing illness, thereby enabling households to maintain income levels rather than causing productivity losses. We cannot fully address the possibility of reverse causality. But since many households are liquidity constrained and struggle to pay health care costs, the plausibility that farming households use pesticides as a compensatory substitute for labor time lost to illnesses independent of pesticides use seems rather unlikely. Furthermore, recall that we consider not only lost labor time on farm and not only for those household members who contribute regularly to farm operations and management; the lost time could be from any work type or household task or member, and there is little reason to believe households would purchase pesticides in response to labor time lost from non-agricultural activities. Even if pesticide use is only associated with reductions in time

[17] We choose five staples from each included country based on frequency of occurrence in the production data and general knowledge about diets. These crops include: Ethiopia-barley, maize, sorghum, teff, wheat; Nigeria-cowpea, cassava, sorghum, maize, millet; Tanzania-maize, sorghum, cassava, cowpeas, millet; and Uganda-maize, cassava, sorghum, millet, banana (food).

spent on farm and the productivity benefits net out favorably, we should still be concerned that pesticide use is related to sickness, no matter the induced labor response.

While it may be tempting to directly compare these two health-related value measures (costs) with the additional value of harvest on account of pesticide use on farm (benefits) described in Section 6.1, these values are not directly comparable because (i) the harvest value estimates are specified at the plot level while health outcomes at the household level, (ii) the magnitude of these values (not the percent changes) would be more instructive for providing a proper cost-benefit analysis, and (iii) we only observe binary pesticide use, not the continuous measure that would be useful for cost-benefit analysis. Moreover, neither of these values necessarily encompasses all potential health-related costs, particularly cumulative, long–term negative effects that may, most extremely, result in premature death.[18] And finally, none of our specifications were set up to offer precise point estimates that would be required for this extension; the interpretation of our analysis should only go as far as the data and estimation will allow.

5.3. Other human health variables

Not all negative human health outcomes correlated with pesticide use will necessarily have a measurable cost associated with them. For that reason, we explore a range of short run human health indicators and display those results in Table 5. As robustness checks and to see to what extent these relationships hold when disaggregating using the same additional variables from the human health cost outcomes, we include our results with income control variable, split by herbicides and non-herbicides (with and without income controls), and for staple crops specifically in Tables A.13-A.16 of the Appendix although focus on the results of our main specifications in the text.

Columns 1-3 show the relationship between *any* day of work lost due to sickness in the very recent past, the binary transformation of the outcome variable contained in columns 4-6 of Table 4. Here

[18] For example, in their sample of smallholder vegetable farmers in Tanzania, Ngowi *et al.* (2007) find far more farmers report sickness related to pesticide use than expenditures related to the medical complications, suggesting that these values will all be lower bounds on the extent of pesticide related monetary losses.

we find positive and statistically significant relationships in nearly all cases, even stronger than the continuous value measures, suggesting that the variability contained within the continuous measures might obscure the fact that members of pesticide-using households do loose more time from work than those in non-pesticide using households.

Columns 4-6 of Table 5 show the correlations between a household member falling sick in the recent past (two months for Ethiopia, one month for Nigeria and Uganda) and pesticide use. In Ethiopia and Nigeria, our preferred specification (column 6) shows remarkable similarity in the positive and statistically significant estimated correlations (at the 10 percent level). In Uganda, these estimates are only positive and significant in the first two specifications (without district effects varying by year). Combined, these results suggest important relationships between using pesticides and the incidence of illness, regardless of whether health expenses were incurred or days from work were lost. This may be our best indicator of "pure" illness associated with pesticides use, as it is unrelated to access to medical facilities and the ability to take time off of work, the trade-off being that there is no way to value and compare this response.

Columns 7-9 of Table 5 explore the relationship between pesticide use and visiting a health worker. In the two countries for which we can isolate visits on account of actual illness over the previous month, Uganda exhibits positive and statistically significant values across all three specifications while Nigeria does only in one of the three. In Ethiopia and Tanzania, we are unable to necessarily distinguish between going to a doctor for preventative or curative care, but the same positive and statistically significant relationships appear. For income and access reasons, we would not expect that all individuals suffering from an illness – related to pesticide exposure or otherwise – would visit a health worker for treatment or advice, and especially not if they consider the negative health effects normal or routine (Banjo *et al.* 2010). However, the fact that this relationship emerges across the four countries under study does point to cause for concern.

While all other variables are related to illness in the recent past, Table 6 attempts to convey the relationship between longer term or chronic sickness and household pesticide use. Because the pesticide use that we observe is contemporaneous and we know nothing about the historic use of this or other inputs, we would not necessarily expect there to be a strong relationship unless pesticide use has been an enduring feature of farm management practices. Furthermore, we are limited to imperfect measures. In Ethiopia, where we find no association, we are only able to correlate the incidence of sickness that lasted more than three months in the last year, which may not encompass all types of chronic illnesses that may arise from pesticide poisoning. In Nigeria, where we find consistently positive and significant associations, the question from which we derive our variable is specific to visiting a health worker because of a long term or chronic illness, implying merely a subset of the cases from Table 6, not all possible chronic illness. The data limitations as well as the null effect in Ethiopia and inexplicable effects in Nigeria illustrate the need for further, more targeted research to replicate and explain these results.

Again we emphasize that we cannot establish a causal relationship with respect to any of these health-related estimates. But the reliable positive association is clear in the data and consistent with both prior evidence from smaller scale data sets tailored to areas where pesticide use was known to be high for a limited set of crops as well as the large toxicology literature. Furthermore, we believe endogeneity-inducing reverse causality – smallholders using pesticides as a substitute for labor when household members experience illness that limits their on farm participation – is highly unlikely due to pervasive liquidity constraints.

6. Conclusions

Using nationally representative panel household survey data from four countries in Sub-Saharan Africa – Ethiopia, Nigeria, Tanzania, and Uganda – this paper explores the relationship between pesticide use on farmers' fields, the value of crop output, and a suite of human health costs and health status indicators. We find consistent evidence that pesticide use is correlated with significantly greater agricultural output value, but also costly from the standpoint of a range of human health outcomes negatively associated with pesticide use and, indirectly, labor supply due to time lost to illness. These results seem particularly profound given the national-level representativeness of our samples, inclusive of farming households across cropping systems and with access to a whole range of pesticides. We expose, perhaps for the first time, that these negative relationships are pervasive beyond just a small selection of crops, like the cotton and rice systems most commonly studied experimentally with small and purposively selected samples, and hold when specifically focusing on pesticides applied to a subset of staples produced in each country.

While we cannot interpret any of our regression estimates as causal, the consistency in our estimated correlations – across samples, specifications, and estimators – combined with how well our findings match intuition, theory, and the existing literature drawn from small and non-representative samples suggests that the causal relationships established by others can likely be attributed to other farming systems across SSA as well. We emphasize that we are not making an assessment of whether observed pesticide application is above or below some optima; such analysis is infeasible in these data. But our regression results are consistent with our conceptual framework in which trade-offs exist and information gaps for farmers might naturally lead to over-application of dangerous pesticides. By highlighting the generalizability of these associations across SSA countries where pesticides are used by at least 10 percent of the farming population, our findings lay a foundation for more detailed exploration and make more urgent the need for multidisciplinary analysis on the health effects of pesticide use in Africa.

Our empirical results highlight that pesticide use is associated with both agricultural output gains and health care costs, including loss of labor power. We cannot tell, however, whether too much chemical is used, or, rather, if the wrong chemicals are being used, or possibly on the wrong targets, in the wrong ways, at the wrong times, or with inadequate protective clothing and equipment or proper storage and handling practices. In many ways, our findings raise more questions than they provide answers. Because we use large-scale nationally representative data from multiple countries, however, our findings clearly signal that (i) pesticide use is becoming widespread in several countries and (ii) there appear productivity-health tradeoffs that should motivate more focused investigations as to why adverse human health effects are now widely associated with pesticides use in African agriculture. Appropriate policy responses will turn on the findings of those more targeted studies.

As indicated in our conceptual framework, overuse would most likely arise from information problems that lead farmers to underestimate the true likely costs of pesticide exposure. Economists who have been able to study these relationships more carefully in other contexts, for example Dasgupta, Meisner, and Huq (2007) in Bangladesh, point to the importance of conveying good and accurate information about the risks of pesticide use, particularly overuse, and doing so using participatory methods. Maumbe and Swinton (2003) also reveal how cotton farmers in Zimbabwe that attend a larger number of extension meetings are more likely to be able to identify the ill-effects of pesticide exposure. At the same time, more judicious use of pesticides due to greater knowledge about ideal application conditions or amounts could also have positive crop output implications, implying even further benefits to household productivity or net income levels, especially if reducing chemical use cuts down on input costs or enables farmers to preserve the natural environment which serves as a platform for their livelihood.

While the LSMS-ISA data allow us, for the first time, to study these correlations across countries, farming systems, crop types, and years, they are imperfect for probing deeper into either causal analysis or unpacking the mechanisms that drive these estimated associations. We offer these findings as a call to other researchers across disciplines to better understand the decision making and behavior that underlie our results using more tailored questionnaires and experiments to help answer the obvious follow-on questions. Are farmers operating without full knowledge of the potential human health costs? Or are the costs theoretically known, but farmers unable to make the link for themselves that the sickness occurring within their households may be driven by the use of pesticides on farm or stored within the family dwelling? Or, perhaps even worse, are they fully aware that household sickness is related to pesticide use but continue to apply despite the known costs (e.g., Wilson and Tisdell 2001)? What can be done to better align knowledge and health outcomes?

We emphasize that our results may under-estimate the negative relationship between human health and pesticides use in rural SSA. First, the set of health variables available to us mostly indicate short term health effects, whereas many of the negative effects of pesticides are known to accrue over the long term. Our results, therefore, likely only shed light on a portion of the fuller set of negative health effects prospectively induced by pesticide use. Second, our study is specific to the crop productivity and human health outcomes for smallholder farming households that use pesticides, not the fuller complement of agricultural laborers who go to work on large commercial or even on other small farms where pesticides are used, nor of rural inhabitants who may suffer from spillover effects due to runoff, contamination, or downwind exposure. Finally, we ignore the disutility of feeling unwell, and therefore likely understate the true cost of pesticide use if it indeed increases the incidence or severity of illness.

From a human health perspective, even the very high incidence of reported sickness we uncover in these four countries, irrespective of pesticide use, merits concern. Structural transformation may be jump-started by agricultural productivity growth, but tending to an unhealthy population is also essential for sustained agricultural and rural non-farm productivity growth and improved standards of living. Where pesticide use may undermine human health status, more focused and intensive investigation of that adverse relationship has merit in order to inform discussions about potential extension and regulatory programming, both within the agricultural and public health arenas. It may prove unwise to promote the use of output-increasing inputs but inadvertently forsake the health, and thereby productivity, of the very individuals who will carry out the structural transformation still yet to truly unfold in rural Africa.

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Table 1: Sample selection, size, and weighting

Country	Survey years included	Number of households in first survey wave	Number of households in full balanced panel	Number of main season ag producing households from full balanced panel
Ethiopia	2011/12 (Y1)	3,969	3,776	2,783
	2013/14 (Y2)			2,994
Nigeria	2010/11 (Y1)	4,916 (both pp, ph)	4,469	2,739
	2012/13 (Y2)			2,814
Tanzania	2008/09 (Y1)	3,265	3,087 (3,742 in Y2, 4,880 in Y3)	2,040
	2010/11 (Y2)			2,320
	2012/13 (Y3)			2,957
Uganda	2009/10 (Y1)	2,975	2,391 (2,391 in Y2, 2,768 in Y3)	1,754
	2010/11 (Y2)			1,913
	2011/12 (Y3)			1,925

Notes: In Nigeria, we consider both portions of data collection (post-planting and post-harvest) when specifying the balanced panel. The main agricultural season chosen for analysis in Tanzania is the long rainy season and the first season in Uganda; only one agricultural season is specified in both the Ethiopia and Nigeria data. In Uganda, a wave of data collected in 2005/06 could be added but we withhold given the time lag and some issues with comparability across rounds. In Tanzania and Uganda, households that "split" from original panel households are tracked and included in the sample. The grayed column is the main sample used in analysis. See Section 4 for more details about these data sets.

Table 2: Key descriptive statistics at household level

Variables	Ethiopia		Nigeria		Tanzania			Uganda		
	Y1	Y2	Y1	Y2	Y1	Y2	Y3	Y1	Y2	Y3
Any pesticide use (binary)	0.31 (0.03)	0.36 (0.03)	0.34 (0.02)	0.38 (0.02)	0.15 (0.01)	0.13 (0.01)	0.14 (0.01)	0.15 (0.01)	0.15 (0.01)	0.15 (0.02)
Herbicide use (binary)	0.27 (0.03)	0.29 (0.03)	0.22 (0.01)	0.26 (0.01)	-	-	-	-	-	-
Pesticide use[¥] (binary)	0.09 (0.02)	0.10 (0.02)	0.19 (0.01)	0.20 (0.01)	-	-	-	-	-	-
Fungicide use (binary)	0.04 (0.01)	0.03 (0.01)	-	-	-	-	-	-	-	-
Value of harvest per hectare (USD)	-	499 (31)	2832 (178)	2198 (185)	201 (33)	204 (13)	205 (7)	396 (91)	269 (29)	363 (89)
Value of health expenditures related to illness (USD)	-	-	5.41 (0.58)	3.54 (0.48)	72.4 (6.20)	67.9 (4.12)	82.6 (5.35)	10.5 (1.29)	6.96 (0.56)	7.23 (0.81)
Value of lost work time due to sickness (USD)	47.0 (3.47)	15.4 (1.03)	19.9 (1.37)	16.4 (1.37)	-	-	-	11.5 (0.64)	8.48 (0.55)	9.38 (0.59)
Number of days lost from work due to sickness	10.6 (0.59)	9.89 (0.57)	3.45 (0.19)	2.90 (0.19)	-	-	-	24.1 (0.79)	16.9 (0.57)	16.2 (0.92)
Any lost days from work due to sickness (binary)	0.47 (0.02)	0.45 (0.02)	0.29 (0.01)	0.28 (0.01)	-	-	-	0.76 (0.01)	0.65 (0.01)	0.66 (0.02)
Recently fell sick (binary)	0.52 (0.02)	0.51 (0.02)	0.46 (0.01)	0.44 (0.01)	-	-	-	0.90 (0.01)	0.80 (0.01)	0.75 (0.02)
Recently visited a health worker (binary)	0.46 (0.02)	0.55 (0.02)	0.30 (0.01)	0.30 (0.10)	0.46 (0.01)	0.50 (0.01)	0.52 (0.01)	0.85 (0.01)	0.74 (0.01)	0.70 (0.02)
Long term/chronic illness (binary)	0.10 (0.01)	0.11 (0.01)	0.07 (0.01)	0.07 (0.01)	-	-	-	-	-	-

Notes: Pesticide use for Tanzania displayed in this table is a combination of long and short rainy season, but mostly driven by long rainy season use, but we use the long rainy season use in the value of harvest model. Pesticide use for Uganda displayed in this table is a combination of the first and second seasons, but we use the first season use in the value of harvest model and the second season for the human health outcomes due to the timing of survey implementation. [¥]See footnote 10 in the main text for details about the use of the term "pesticide" in the Ethiopia and Nigeria data.

Table 3: Value of harvest (plot/parcel level)

	(1) Value of harvest (USD)	(2) Value of harvest (USD)	(3) Value of harvest (USD)	(4) LN Value of harvest (USD)	(5) LN Value of harvest (USD)	(6) LN Value of harvest (USD)
			Ethiopia			
Pesticide on plot = 1	31.67***	29.63***	18.55***	0.704***	0.697***	0.333***
	(3.443)	(3.190)	(2.914)	(0.0469)	(0.0443)	(0.0395)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	No	No	Yes	No	No
Household FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
			Nigeria			
Pesticide on plot = 1	84.55***	67.70**	41.65	0.188***	0.180**	0.0671
	(27.00)	(27.94)	(26.78)	(0.0723)	(0.0719)	(0.0706)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
			Tanzania			
Pesticide on plot = 1	62.16***	60.47***	39.70***	0.429***	0.424***	0.328***
	(7.854)	(7.661)	(7.306)	(0.0601)	(0.0599)	(0.0576)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
			Uganda			
Pesticide on prcl = 1	51.52***	46.11***	37.73***	0.441***	0.393***	0.333***
	(10.58)	(9.566)	(8.819)	(0.0847)	(0.0826)	(0.0830)
Parcel level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parentheses) clustered at the household level. All regressions run at the plot (Ethiopia, Nigeria, and Tanzania) or parcel (Uganda) level. Full results available in the Appendix (Ethiopia in Table A.2., Nigeria in Table A.3, Tanzania in Table A.4, and Uganda in Table A.5).

Table 4: Value of measurable human health costs (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1				0.211	0.284*	0.316*			
				(0.157)	(0.166)	(0.166)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Pesticide use = 1	0.114	0.247**	0.275**	0.398**	0.118	0.144	0.212	0.154	0.184
	(0.110)	(0.125)	(0.125)	(0.188)	(0.215)	(0.217)	(0.140)	(0.161)	(0.163)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1	0.368***	0.511***	0.509***						
	(0.0949)	(0.0957)	(0.0960)						
Year FE	Yes	Yes	Yes						
Region FE	No	Yes	No						
Region*year FE	No	No	Yes						
Uganda									
Pesticide use = 1	0.763***	0.599***	0.576***	0.510***	0.244*	0.215	0.631***	0.383***	0.349***
	(0.186)	(0.142)	(0.128)	(0.183)	(0.136)	(0.135)	(0.180)	(0.137)	(0.132)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions. Various robustness checks can be found in the Appendix.

Table 5: Other short run human health indicators (household level)

	Any work day lost due to sickness (=1)			Recently fell sick (=1)			Recently visited a health worker (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1	0.0367*	0.0431**	0.0468**	0.0294	0.0336	0.0367*	0.0376*	0.0249	0.0271
	(0.0201)	(0.0208)	(0.0207)	(0.0196)	(0.0204)	(0.0204)	(0.0193)	(0.0200)	(0.0201)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Nigeria									
Pesticide use = 1	0.0382***	0.0183	0.0191	0.0210	0.0335*	0.0343*	0.0311**	0.0232	0.0263
	(0.0148)	(0.0166)	(0.0168)	(0.0161)	(0.0182)	(0.0185)	(0.0150)	(0.0171)	(0.0170)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1							0.0696***	0.0768***	0.0756***
							(0.0188)	(0.0190)	(0.0191)
Year FE							Yes	Yes	Yes
Region FE							No	Yes	No
Region*year FE							No	No	Yes
Uganda									
Pesticide use = 1	0.0886**	0.0637*	0.0627*	0.0788***	0.0522**	0.0395	0.128***	0.107***	0.0950***
	(0.0374)	(0.0351)	(0.0335)	(0.0275)	(0.0265)	(0.0263)	(0.0285)	(0.0274)	(0.0276)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions. All estimated via OLS. Various robustness checks can be found in the Appendix.

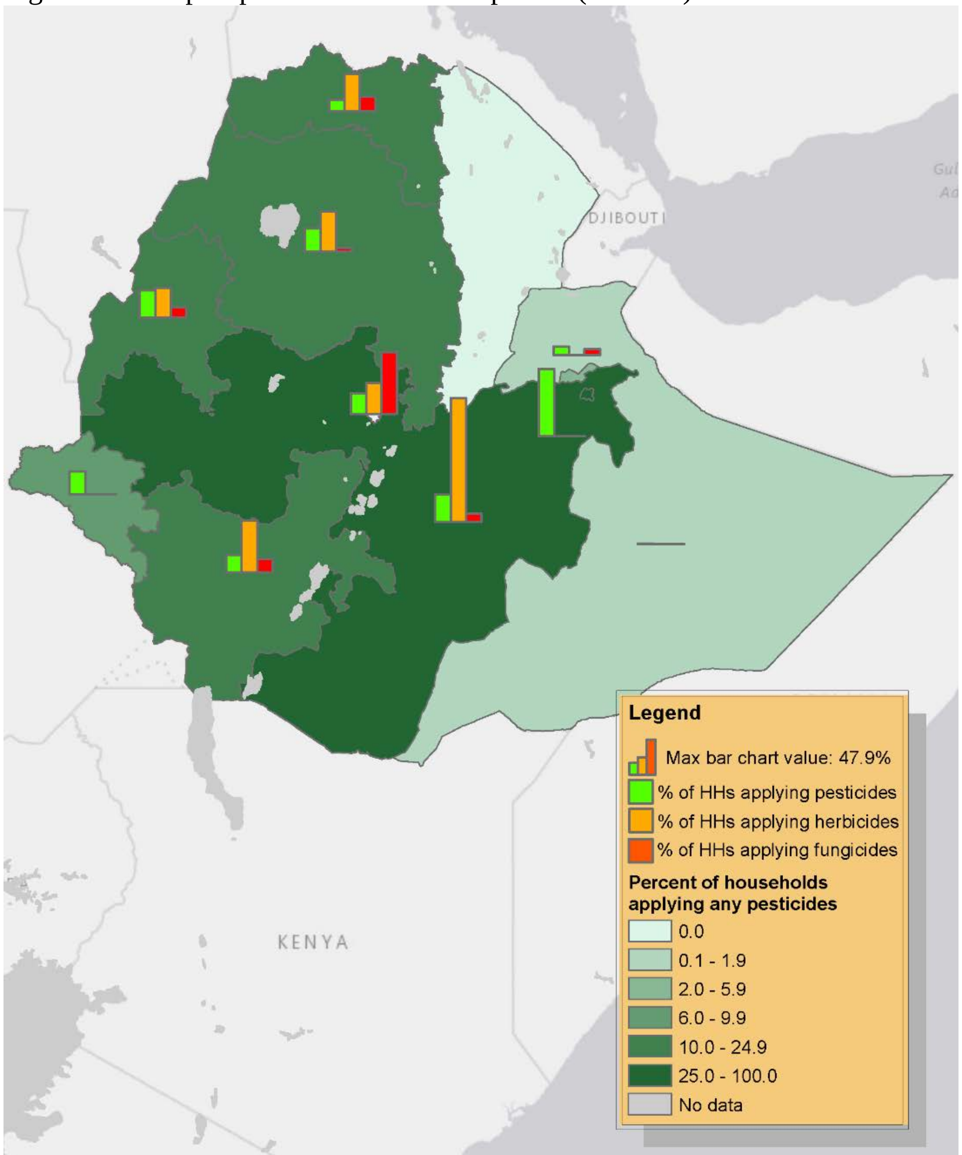
Table 6: Other long run health indicators (household level)

	Chronic or long term sickness (=1)		
	(1)	(2)	(3)
Ethiopia			
Pesticide use = 1	-0.0133	-0.0144	-0.0144
	(0.0117)	(0.0126)	(0.0125)
Year FE	Yes	Yes	Yes
State FE	No	Yes	No
State*year FE	No	No	Yes
Nigeria			
Pesticide use = 1	0.0228**	0.0195**	0.0217**
	(0.00901)	(0.00886)	(0.00916)
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Region*year FE	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions. All estimated with OLS. Various robustness checks can be found in the Appendix.

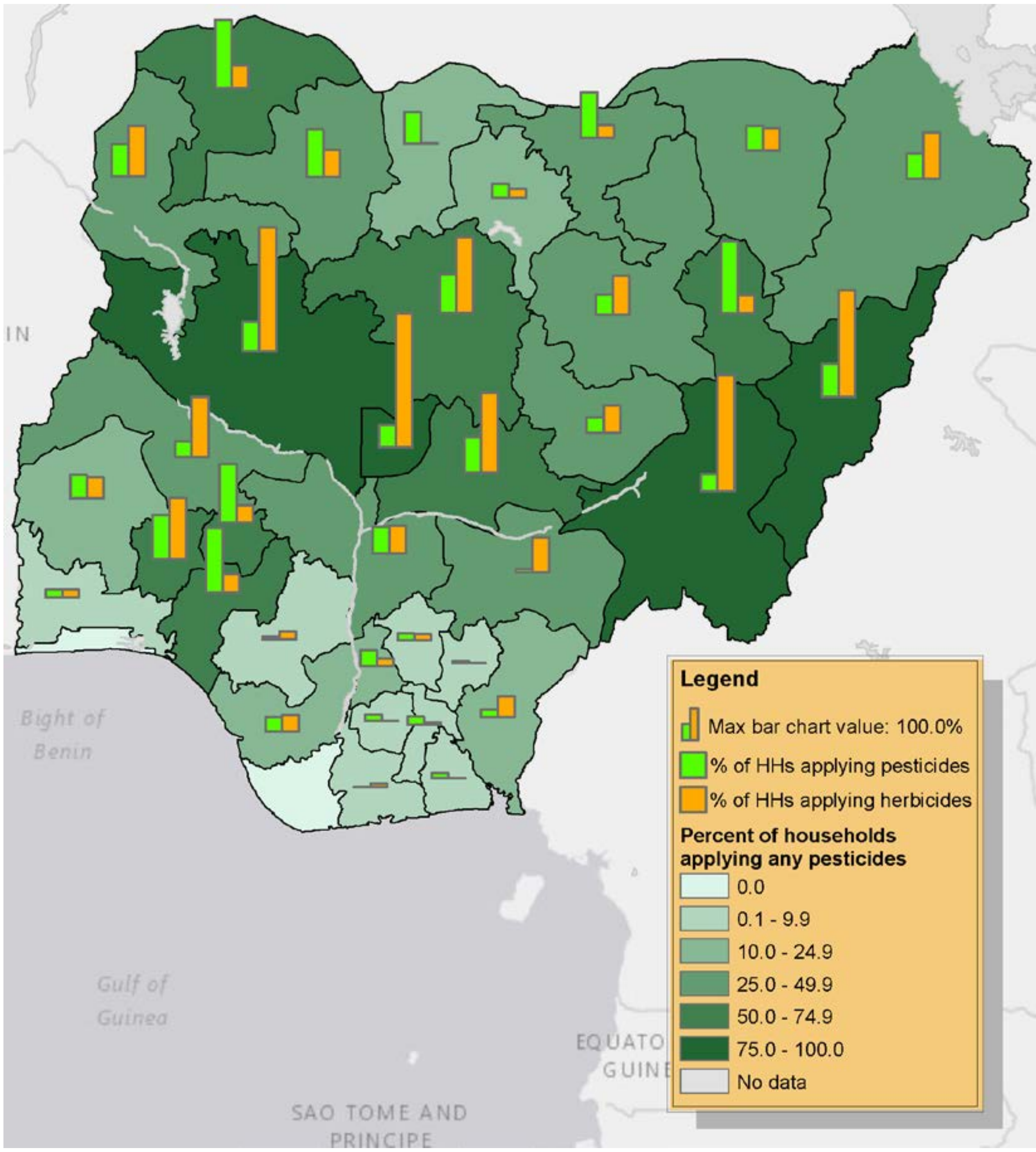
Appendix: Supplementary figures and tables

Figure A.1: Map of pesticide use in Ethiopia Y1 (2011/12) cross section



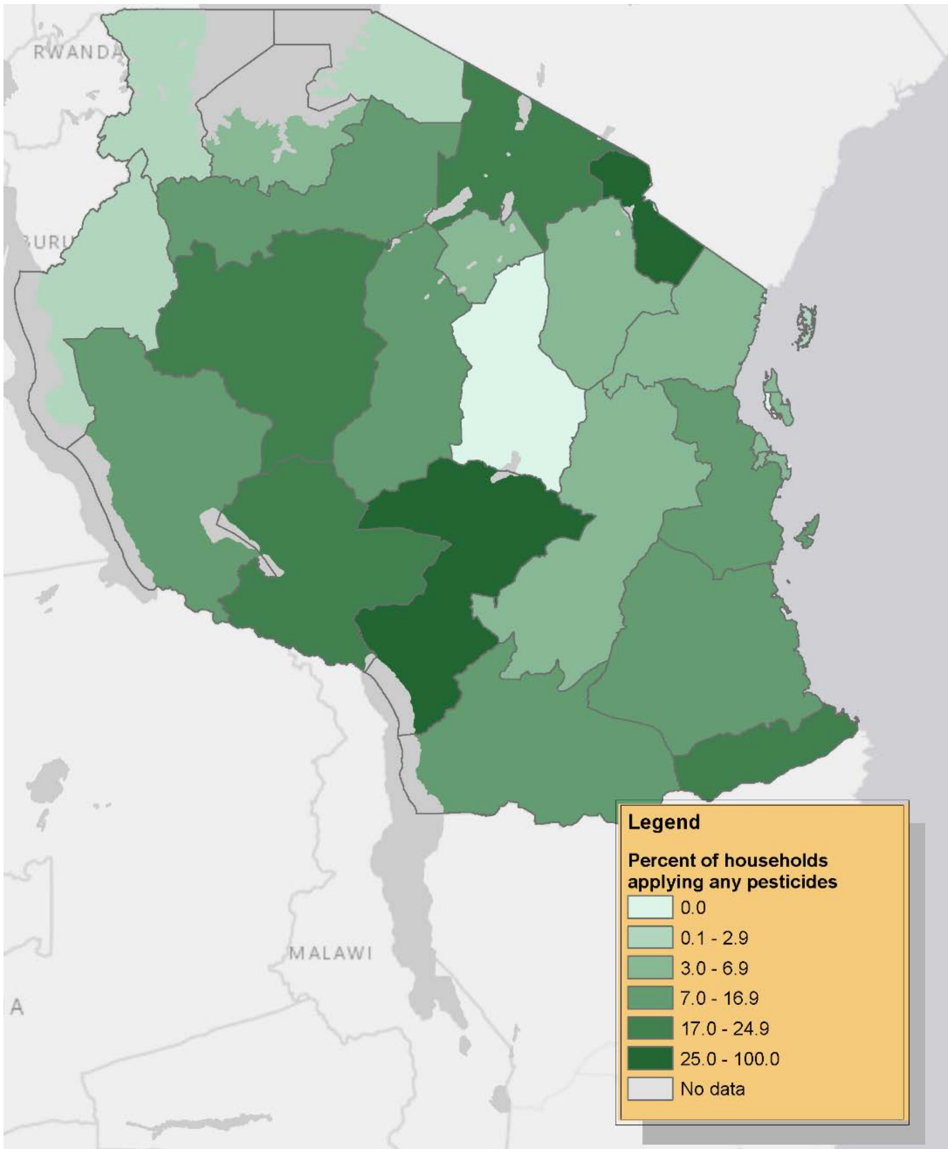
Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Ethiopia 2011/12.

Figure A.2: Map of pesticide use in Nigeria Y1 (2010/11) cross section



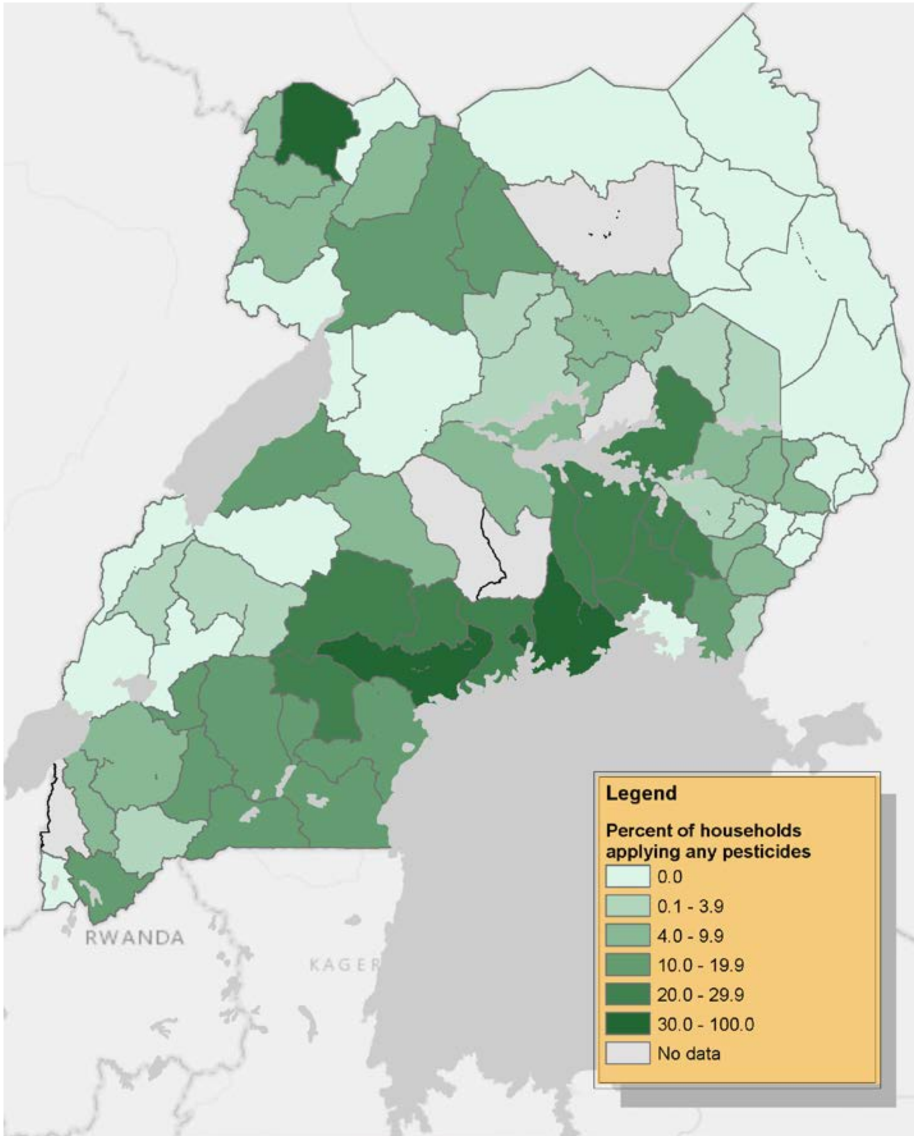
Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Nigeria 2010/11.

Figure A.3: Map of pesticide use in Tanzania Y2 (2010/11) cross section



Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Tanzania 2010/11.

Figure A.4: Map of pesticide use in Uganda Y2 (2010/11) cross section



Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Uganda 2010/11.

Table A.1: Cross-country comparison of survey questions used to create human health variables

	Ethiopia	Nigeria	Tanzania	Uganda
Value of health expenses	N/A	Amount spent on first consultation with health worker related to illness in last 4 weeks (we can exclude injuries)[2]	Amount spent on illness/injuries in the last 4 weeks (observed at individual level, then aggregated to household level)	Amount spent on illness/injuries in the last 30 days (observed at individual level, then aggregated to household level)
Value of lost work time due to sickness	Number of days absent from usual activities due to health problem experienced in last 2 months (we can exclude injuries and dental related), multiplied by median	For how many days in the last 4 weeks did you have to stop usual activities in last 4 weeks due to illness (we can exclude injuries), multiplied	N/A	Number of days lost from normal activities in last 30 days due to illness/injury, multiplied by median agricultural wage (aggregated across

	harvest wage split by gender	by median harvest wage split by gender		activities) in first season
Number of days lost from work time due to sickness	Number of days absent from usual activities due to health problem experienced in last 2 months (we can exclude injuries and dental related)	For how many days in the last 4 weeks did you have to stop usual activities in last 4 weeks due to illness (we can exclude injuries)	N/A	Number of days lost from normal activities in last 30 days due to illness/injury
Out sick from work due to sickness (binary)	Did you stop your usual activities due to health problems in last 2 months (we can exclude injuries and dental related)	Did you need to stop your usual activities for an illness in last 4 weeks (we can exclude injury)	N/A[3]	Did you need to stop normal activities in last 30 days due to illness/injury
Recently fell sick (binary)	Individual faced a health problem in last 2 months (we can exclude injuries and dental related)	Individual fell sick due to illness in last 4 weeks (we can exclude injuries)	N/A	Illness or injury in last 30 days, (can only exclude injuries related to fractures)
Visited a health worker (binary)	Visited health worker in last 2 months (not specific to illness)[1]	Consulted a health practitioner in the last 4 weeks, only for new illness, chronic illness, or other	Visited a health care provider in last 4 weeks (not specific to illness)	Consulted someone about illness/injury, conditional on having one in last 30 days
Long term or chronic illness (binary)	Been sick for 3 consecutive months of last 12 months (excluding accidents)	Consulted a health practitioner in last 4 weeks due to chronic illness (not inclusive of all chronic illness effects)	N/A	N/A

Notes: [1]There is also a variable related to visiting a health worker over the last 12 months, but we do not include it. [2]A health expenditure aggregate is included with this data set. We choose not to use it because it includes a range of other expenses, including those related to preventative or routine care. [3]There is a question that solicits if an individual did not go to work in the last week, but the time frame is too narrow to be comparable with other countries or commensurate with the agricultural season. Only between 4-10 percent of our sample had a non-zero value here.

Table A.2: Value of harvest in Ethiopia (full regression results)

	(1) Value of harvest (USD)	(2) Value of harvest (USD)	(3) Value of harvest (USD)	(4) LN Value of harvest (USD)	(5) LN Value of harvest (USD)	(6) LN Value of harvest (USD)
Pesticide on plot = 1	31.67***	29.63***	18.55***	0.704***	0.697***	0.333***
	(3.443)	(3.190)	(2.914)	(0.0469)	(0.0443)	(0.0395)
Chemical fertilizer (kg/ha)	0.0434***	0.0402***	0.0282***	0.00111***	0.000786***	0.000416***
	(0.00686)	(0.00645)	(0.00601)	(0.000122)	(0.000119)	(0.0000972)
Organic fertilizer = 1	-7.308***	-7.606***	-2.976**	-0.312***	-0.411***	-0.190***
	(1.303)	(1.460)	(1.385)	(0.0308)	(0.0324)	(0.0295)
Plot size (ha)	96.63***	85.42***	70.04***	1.491***	1.455***	1.054***
	(12.29)	(11.39)	(10.12)	(0.163)	(0.175)	(0.139)
Plot size (ha) – squared	-5.095***	-4.075***	-3.364***	-0.0785***	-0.0703***	-0.0502***
	(0.657)	(0.584)	(0.524)	(0.00909)	(0.00925)	(0.00751)
No. of crops on field	8.174***	7.789***	-105.1***	0.302***	0.336***	-0.995***
	(1.092)	(1.221)	(14.83)	(0.0219)	(0.0218)	(0.273)
Maize plot = 1	-4.686*	-6.730**	-5.025	-0.216***	-0.227***	-0.236***
	(2.665)	(2.663)	(3.164)	(0.0498)	(0.0526)	(0.0648)
Teff plot = 1	19.43***	17.84***	-16.53**	0.168***	0.101	-0.593***
	(3.593)	(3.455)	(7.802)	(0.0612)	(0.0637)	(0.114)
Sorghum plot = 1	18.85***	8.684***	-8.457*	0.111**	-0.00554	-0.337***
	(4.039)	(3.307)	(4.957)	(0.0556)	(0.0599)	(0.0793)
Coffee plot = 1	1.410	1.895	-5.427*	-0.0987*	-0.109*	-0.338***
	(2.851)	(2.853)	(3.069)	(0.0537)	(0.0559)	(0.0662)
Other plot = 1	-3.670	-8.893**	-12.10**	-0.633***	-0.751***	-0.961***
	(4.031)	(3.953)	(4.896)	(0.0678)	(0.0710)	(0.102)
Irrigated = 1	-2.720	3.576	6.358*	0.0347	0.0105	0.108
	(3.737)	(3.998)	(3.800)	(0.0854)	(0.0968)	(0.0778)
Leptosol soil = 1	-10.26	10.76	8.394	-0.136	0.212**	0.171*
	(7.659)	(6.661)	(6.486)	(0.109)	(0.104)	(0.0905)
Cambisol soil = 1	-12.12	10.55	11.45*	-0.0904	0.189	0.187
	(7.755)	(6.500)	(6.604)	(0.123)	(0.137)	(0.129)
Vertisol soil = 1	-0.889	8.491	7.758	0.0400	0.160*	0.130
	(7.402)	(5.963)	(6.047)	(0.102)	(0.0950)	(0.0833)
Luvisol soil = 1	-6.840	4.108	3.952	-0.101	0.0684	0.0592
	(7.207)	(5.962)	(6.023)	(0.102)	(0.0962)	(0.0835)
Mixed type soil = 1	-6.765	6.246	5.663	-0.0259	0.172*	0.146
	(7.711)	(6.525)	(6.545)	(0.107)	(0.101)	(0.0896)
Good quality soil = 1	3.712*	6.948**	7.681***	0.0420	0.00994	0.0487
	(2.120)	(2.806)	(2.642)	(0.0403)	(0.0511)	(0.0464)
Fair quality soil = 1	4.877**	5.930**	5.870**	0.0959**	0.0496	0.0547
	(2.042)	(2.528)	(2.322)	(0.0380)	(0.0441)	(0.0387)
Constant	27.69***	12.69*	14.85*	2.978***	2.773***	2.749***
	(9.288)	(7.591)	(7.731)	(0.137)	(0.124)	(0.123)
Region FE	Yes	No	No	Yes	No	No
Household FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
No obs.	20,327	20,327	20,327	20,327	20,327	20,327
No hh.	2,994	2,994	2,994	2,994	2,994	2,994
R-squared	0.240	0.185	0.287	0.336	0.296	0.433

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level.

Table A.3: Value of harvest in Nigeria (full regression results)

	(1) Value of harvest (USD)	(2) Value of harvest (USD)	(3) Value of harvest (USD)	(4) LN Value of harvest (USD)	(5) LN Value of harvest (USD)	(6) LN Value of harvest (USD)
Pesticide on plot = 1	84.55***	67.70**	41.65	0.188***	0.180**	0.0671
	(27.00)	(27.94)	(26.78)	(0.0723)	(0.0719)	(0.0706)
Chemical fertilizer (kg/ha)	0.0409	0.150**	0.116*	0.000132	0.000319*	0.0000904
	(0.0613)	(0.0645)	(0.0631)	(0.000176)	(0.000173)	(0.000158)
Organic fertilizer = 1	4.248	-46.88	-19.57	0.0643	0.0271	0.0202
	(52.24)	(52.30)	(49.12)	(0.182)	(0.180)	(0.174)
Plot size (ha)	341.6***	370.3***	326.2***	0.930***	0.895***	0.597***
	(74.85)	(78.37)	(74.98)	(0.185)	(0.172)	(0.162)
Plot size (ha) – squared	-54.51	-86.54**	-68.61*	-0.212***	-0.253***	-0.154**
	(37.64)	(39.63)	(36.60)	(0.0761)	(0.0719)	(0.0690)
No. of crops on plot	97.77***	90.65***	10.23	0.333***	0.295***	-0.137***
	(13.35)	(13.22)	(13.06)	(0.0333)	(0.0341)	(0.0359)
Maize plot = 1	-76.12***	-72.78***	-32.68	-0.142***	-0.109**	-0.00360
	(25.20)	(23.93)	(21.98)	(0.0528)	(0.0501)	(0.0476)
Cassava plot = 1	-57.69**	-65.67***	-20.99	-0.257***	-0.289***	-0.0660
	(24.68)	(23.85)	(23.51)	(0.0657)	(0.0617)	(0.0581)
Cowpea plot = 1	-39.44	-49.12**	-40.14*	-0.0136	-0.0193	0.0409
	(24.07)	(23.28)	(21.89)	(0.0701)	(0.0641)	(0.0620)
Sorghum plot = 1	-31.57	-24.93	9.792	-0.0634	-0.0360	0.0482
	(25.94)	(25.47)	(25.62)	(0.0687)	(0.0632)	(0.0626)
Irrigated = 1	205.8	194.0	72.92	-0.139	-0.153	-0.0499
	(139.6)	(142.6)	(63.62)	(0.212)	(0.218)	(0.173)
Animal traction on plot = 1	-16.60	-0.124	13.24	-0.0122	-0.00330	0.0233
	(32.91)	(32.23)	(30.48)	(0.105)	(0.0977)	(0.101)
Machines used on plot = 1	-27.31	18.11	-12.66	-0.142	0.0334	-0.0218
	(37.59)	(38.26)	(34.09)	(0.100)	(0.103)	(0.102)
Constant	164.3***	188.3***	124.6**	3.951***	3.831***	3.655***
	(48.62)	(50.51)	(59.57)	(0.131)	(0.227)	(0.199)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
No. obs	10,599	10,599	10,599	10,599	10,599	10,599
No. hh	3,083	3,083	3,083	3,083	3,083	3,083
R-sq	0.043	0.078	0.200	0.052	0.096	0.303

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level.

Table A.4: Value of harvest in Tanzania (full regression results)

	(1) Value of harvest (USD)	(2) Value of harvest (USD)	(3) Value of harvest (USD)	(4) LN Value of harvest (USD)	(5) LN Value of harvest (USD)	(6) LN Value of harvest (USD)
Pesticide on plot = 1	62.16***	60.47***	39.70***	0.429***	0.424***	0.328***
	(7.854)	(7.661)	(7.306)	(0.0601)	(0.0599)	(0.0576)
Chemical fertilizer (kg/ha)	0.292***	0.284***	0.213***	0.00153***	0.00148***	0.00119***
	(0.0728)	(0.0672)	(0.0521)	(0.000335)	(0.000331)	(0.000252)
Organic fertilizer = 1	7.806	7.342	6.997	0.130**	0.129**	0.0989**
	(5.485)	(5.298)	(5.168)	(0.0556)	(0.0554)	(0.0486)
Irrigated = 1	19.06	18.35	17.01	0.420***	0.404***	0.466***
	(15.33)	(15.63)	(15.45)	(0.143)	(0.144)	(0.145)
Plot size (ha)	10.27***	10.90***	8.975***	0.0641***	0.0675***	0.0469***
	(2.245)	(2.193)	(2.041)	(0.0151)	(0.0147)	(0.0130)
Plot size (ha) – squared	-0.0406***	-0.0429***	-0.0356***	-0.000246***	-0.000255***	-0.000184***
	(0.00922)	(0.00907)	(0.00841)	(0.0000643)	(0.0000629)	(0.0000554)
No. of crops on plot	39.10***	38.48***	3.579	0.454***	0.453***	-1.344***
	(3.780)	(3.807)	(5.621)	(0.0274)	(0.0276)	(0.0696)
Maize plot = 1	3.865	3.783	7.005	0.247***	0.234***	0.135***
	(4.296)	(4.276)	(4.652)	(0.0376)	(0.0377)	(0.0365)
Rice plot = 1	85.64***	83.78***	32.38**	1.098***	1.078***	0.401***
	(7.980)	(7.875)	(13.03)	(0.0670)	(0.0667)	(0.0876)
Other plot = 1	6.614	5.232	-3.121	-0.0679	-0.104	-0.0365
	(5.901)	(5.930)	(7.191)	(0.0706)	(0.0713)	(0.0690)
Cassava plot = 1	0.854	1.636	-7.078	-0.305***	-0.294***	-0.267***
	(5.720)	(5.534)	(7.961)	(0.0630)	(0.0627)	(0.0956)
Sandy soil = 1	-1.692	-6.433	-2.198	-0.133	-0.147	-0.0553
	(11.26)	(11.11)	(10.44)	(0.127)	(0.126)	(0.109)
Loam soil = 1	6.366	0.342	3.826	-0.0881	-0.129	-0.0664
	(11.12)	(11.04)	(10.38)	(0.123)	(0.122)	(0.105)
Clay soil = 1	11.70	5.589	6.810	0.00573	-0.0308	0.00463
	(11.63)	(11.46)	(10.81)	(0.128)	(0.127)	(0.110)
Good soil quality = 1	16.11***	16.84***	13.99***	0.251***	0.259***	0.254***
	(5.642)	(5.654)	(5.259)	(0.0715)	(0.0720)	(0.0647)
Average soil quality = 1	6.142	6.264	5.370	0.114	0.114	0.128**
	(5.669)	(5.665)	(5.241)	(0.0695)	(0.0698)	(0.0620)
Flat bottom slope = 1	-5.786	-9.506	-8.580	0.0156	-0.00457	-0.0656
	(6.937)	(6.773)	(6.498)	(0.0946)	(0.0912)	(0.0813)
Flat top slope = 1	-5.683	-10.72	-9.381	0.0611	0.0108	-0.0588
	(8.011)	(7.883)	(7.520)	(0.103)	(0.0994)	(0.0907)
No slope = 1	-4.624	-6.914	-5.948	0.0801	0.0551	-0.000707
	(6.728)	(6.517)	(6.154)	(0.0897)	(0.0869)	(0.0790)
Eroded field = 1	3.819	4.059	3.303	0.122**	0.134***	0.104**
	(4.478)	(4.449)	(4.427)	(0.0487)	(0.0481)	(0.0450)
Constant	-1.840	74.04	116.7*	2.467***	3.482***	3.635***
	(13.79)	(49.33)	(62.01)	(0.165)	(0.368)	(0.361)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
No. obs	14,659	14,659	14,659	14,659	14,659	14,659
No. hh	2,379	2,379	2,379	2,379	2,379	2,379
R-sq	0.127	0.147	0.198	0.137	0.152	0.296

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level.

Table A.5: Value of harvest in Uganda (full regression results)

	(1) Value of harvest (USD)	(2) Value of harvest (USD)	(3) Value of harvest (USD)	(4) LN Value of harvest (USD)	(5) LN Value of harvest (USD)	(6) LN Value of harvest (USD)
Pesticide on prcl = 1	51.52***	46.11***	37.73***	0.441***	0.393***	0.333***
	(10.58)	(9.566)	(8.819)	(0.0847)	(0.0826)	(0.0830)
Chemical fertilizer (kg/ha)	0.147**	0.110	0.0866	0.00211***	0.00164**	0.00131**
	(0.0702)	(0.0703)	(0.0624)	(0.000659)	(0.000636)	(0.000525)
Organic fertilizer = 1	22.06***	21.61***	18.76***	0.150**	0.161***	0.161***
	(7.380)	(6.837)	(6.551)	(0.0642)	(0.0617)	(0.0621)
Parcel size (ha)	14.87**	17.95***	19.31***	0.163***	0.204***	0.198***
	(6.689)	(5.677)	(5.383)	(0.0554)	(0.0527)	(0.0514)
Parcel size (ha) – squared	1.435	0.454	0.253	-0.0138*	-0.0201***	-0.0170**
	(1.764)	(1.125)	(1.102)	(0.00736)	(0.00708)	(0.00710)
No. of crops on parcel	18.54***	18.55***	9.674*	0.253***	0.252***	0.0556*
	(1.635)	(1.532)	(5.340)	(0.0128)	(0.0126)	(0.0303)
Maize parcel = 1	-1.844	-3.182	-6.763	0.531***	0.510***	0.427***
	(5.124)	(5.071)	(5.274)	(0.0873)	(0.0834)	(0.0840)
Banana parcel = 1	2.873	2.222	-2.571	0.545***	0.540***	0.465***
	(5.377)	(5.087)	(5.057)	(0.0857)	(0.0812)	(0.0815)
Cassava parcel = 1	-0.576	-2.863	-2.964	0.401***	0.393***	0.438***
	(5.532)	(5.273)	(5.548)	(0.0889)	(0.0836)	(0.0878)
Other parcel = 1	-0.0381	-0.858	-6.194	0.881***	0.877***	0.839***
	(9.538)	(9.118)	(9.845)	(0.167)	(0.161)	(0.165)
Sandy loam soil = 1	10.08	2.973	5.044	0.0990	0.0952	0.137*
	(7.711)	(6.673)	(6.903)	(0.0943)	(0.0756)	(0.0753)
Sandy clay loam soil = 1	19.97**	11.25	11.72*	0.193**	0.167**	0.206***
	(7.801)	(6.875)	(6.873)	(0.0944)	(0.0748)	(0.0744)
Black clay soil = 1	21.16**	14.59**	14.01*	0.251**	0.232***	0.264***
	(9.901)	(7.383)	(7.540)	(0.0992)	(0.0768)	(0.0770)
Good soil quality = 1	11.88*	14.93**	11.74	0.230**	0.230**	0.171*
	(6.660)	(7.348)	(7.464)	(0.106)	(0.102)	(0.0997)
Fair soil quality = 1	1.522	2.852	1.809	0.150	0.146	0.107
	(6.767)	(7.546)	(7.653)	(0.102)	(0.0981)	(0.0966)
Hilly = 1	-21.78	-12.95	-11.35	-0.166	-0.150	-0.128
	(13.55)	(10.94)	(10.68)	(0.106)	(0.102)	(0.0992)
Flat = 1	-17.79	-12.63	-13.95	-0.124	-0.147	-0.171*
	(15.15)	(11.05)	(10.74)	(0.105)	(0.100)	(0.0986)
Gentle slope = 1	-20.05	-15.85	-17.13	-0.0966	-0.116	-0.133
	(14.52)	(10.89)	(10.66)	(0.0985)	(0.0967)	(0.0949)
Valley = 1	-26.03	-18.47	-19.54	-0.222	-0.201	-0.220
	(16.85)	(14.37)	(13.82)	(0.149)	(0.148)	(0.141)
Irrigated = 1	8.224	9.171	2.125	0.191*	0.133	0.0271
	(13.14)	(13.10)	(14.48)	(0.111)	(0.112)	(0.123)
Swamp/wetland = 1	25.45	26.18	19.63	0.337**	0.309*	0.274*
	(17.18)	(17.13)	(17.18)	(0.158)	(0.159)	(0.155)
Eroded = 1	-1.714	0.570	1.756	0.0255	0.0384	0.0534
	(4.343)	(4.519)	(4.408)	(0.0593)	(0.0549)	(0.0527)
Constant	22.90	-17.10	-106.6***	1.815***	1.491***	-1.960***
	(18.23)	(28.29)	(19.58)	(0.204)	(0.431)	(0.357)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
No. obs.	10,306	10,306	10,306	10,306	10,306	10,306
No. hh	2,034	2,034	2,034	2,034	2,034	2,034
R-sq	0.155	0.242	0.271	0.196	0.260	0.299

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level.

Table A.6: Value of harvest per hectare on account of pesticide use (plot/parcel level)

	(1) Value of harvest (USD) per hectare	(2) Value of harvest (USD) per hectare	(3) Value of harvest (USD) per hectare	(4) LN Value of harvest (USD) per hectare	(5) LN Value of harvest (USD) per hectare	(6) LN Value of harvest (USD) per hectare
Ethiopia						
Pesticide on plot = 1	63.82**	4.281	40.23	0.284***	0.237***	0.147***
	(28.76)	(36.21)	(33.43)	(0.0400)	(0.0417)	(0.0419)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	No	No	Yes	No	No
Household FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
Nigeria						
Pesticide on plot = 1	268.1***	201.5**	144.2*	0.188**	0.163*	0.0364
	(84.77)	(86.78)	(82.26)	(0.0863)	(0.0872)	(0.0864)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
Tanzania						
Pesticide on plot = 1	34.18***	36.21***	24.61**	0.245***	0.240***	0.190***
	(12.17)	(12.27)	(12.39)	(0.0654)	(0.0649)	(0.0583)
Plot level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes
Uganda						
Pesticide on prcl = 1	100.1**	93.89**	51.51	0.372***	0.320***	0.246***
	(40.01)	(38.12)	(31.36)	(0.0941)	(0.0879)	(0.0917)
Parcel level controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District*year FE	No	Yes	Yes	No	Yes	Yes
Crop-type FE	No	No	Yes	No	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parentheses) clustered at the household level. All regressions run at the plot (Ethiopia, Nigeria, and Tanzania) or parcel (Uganda) level.

Table A.7: Number of days lost from work due to illness/sickness (household level)

	(1)	(2)	(3)
		Ethiopia	
Pesticide use = 1	0.174	0.201	0.225*
	(0.125)	(0.133)	(0.132)
Year FE	Yes	Yes	Yes
State FE	No	Yes	No
State*year FE	No	No	Yes
		Nigeria	
Pesticide use = 1	0.277**	0.0890	0.100
	(0.118)	(0.136)	(0.137)
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Region*year FE	No	No	Yes
		Uganda	
Pesticide use = 1	0.366***	0.228**	0.181
	(0.138)	(0.115)	(0.113)
Year FE	Yes	Yes	Yes
District FE	No	Yes	No
District*year FE	No	No	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions.

Table A.8: Value of measurable human health costs – OLS robustness check (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1				0.0659	0.107	0.122			
				(0.0734)	(0.0777)	(0.0775)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Pesticide use = 1	-0.0199	0.0368	0.0533	0.0860	0.00271	0.0139	0.0639	0.0195	0.0342
	(0.0343)	(0.0378)	(0.0374)	(0.0545)	(0.0603)	(0.0616)	(0.0573)	(0.0636)	(0.0648)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1	0.293***	0.390***	0.388***						
	(0.0749)	(0.0754)	(0.0758)						
Year FE	Yes	Yes	Yes						
Region FE	No	Yes	No						
Region*year FE	No	No	Yes						
Uganda									
Pesticide use = 1	0.531***	0.433***	0.422***	0.389***	0.169	0.147	0.507***	0.302**	0.276**
	(0.135)	(0.111)	(0.0956)	(0.145)	(0.103)	(0.102)	(0.158)	(0.119)	(0.114)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions.

Table A.9: Value of measurable human health costs – with income control variable (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1				0.173	0.251	0.287*			
				(0.159)	(0.168)	(0.167)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Pesticide use = 1	0.132	0.177	0.212	0.556***	0.288	0.321	0.308**	0.185	0.213
	(0.121)	(0.135)	(0.134)	(0.209)	(0.235)	(0.233)	(0.156)	(0.176)	(0.178)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1	0.154*	0.350***	0.345***						
	(0.0929)	(0.0945)	(0.0948)						
Year FE	Yes	Yes	Yes						
Region FE	No	Yes	No						
Region*year FE	No	No	Yes						
Uganda									
Pesticide use = 1	0.655***	0.484***	0.464***	0.502***	0.237*	0.210	0.587***	0.336**	0.304**
	(0.188)	(0.143)	(0.127)	(0.188)	(0.140)	(0.139)	(0.184)	(0.140)	(0.136)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions. No income control variable is available for Ethiopia, so the consumption aggregate is used as a proxy.

Table A.10: Value of measurable human health costs – by pesticide type (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Herbicide = 1				0.334**	0.420**	0.407**			
				(0.160)	(0.172)	(0.171)			
Other pesticide = 1				-0.391	-0.343	-0.272			
				(0.257)	(0.257)	(0.257)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Herbicide use = 1	0.173	0.255*	0.262*	0.772***	0.277	0.305	0.438***	0.289	0.315*
	(0.116)	(0.141)	(0.142)	(0.197)	(0.238)	(0.237)	(0.150)	(0.185)	(0.187)
Other pesticide = 1	0.0488	0.249*	0.253*	-0.325	0.0391	0.0113	-0.126	0.107	0.0951
	(0.142)	(0.151)	(0.151)	(0.240)	(0.245)	(0.243)	(0.178)	(0.185)	(0.187)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions. Breakdown only available for Ethiopia and Nigeria.

Table A.11: Value of measurable human health costs – by pesticide type with income control variable (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Herbicide = 1				0.302*	0.393**	0.382**			
				(0.162)	(0.172)	(0.172)			
Other pesticide = 1				-0.427*	-0.378	-0.305			
				(0.258)	(0.258)	(0.258)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Herbicide use = 1	0.177	0.175	0.176	0.794***	0.227	0.215	0.474***	0.229	0.221
	(0.126)	(0.152)	(0.152)	(0.219)	(0.264)	(0.263)	(0.166)	(0.203)	(0.205)
Other pesticide = 1	0.134	0.266	0.272*	-0.0799	0.369	0.389	0.0522	0.268	0.272
	(0.155)	(0.165)	(0.164)	(0.261)	(0.263)	(0.259)	(0.195)	(0.203)	(0.205)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions. Breakdown only available for Ethiopia and Nigeria. No income control variable is available for Ethiopia, so the consumption aggregate is used as a proxy.

Table A.12: Value of measurable human health costs – on staples (household level)

	Value of health expenditures from sickness (USD)			Value of lost work time from sickness (USD)			Combined costs (USD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use on staples = 1				0.304*	0.372**	0.378**			
				(0.157)	(0.167)	(0.167)			
Year FE				Yes	Yes	Yes			
State FE				No	Yes	No			
State*year FE				No	No	Yes			
Nigeria									
Pesticide use on staples = 1	0.190	0.301**	0.338**	0.432**	0.0972	0.119	0.286*	0.179	0.221
	(0.123)	(0.138)	(0.138)	(0.207)	(0.231)	(0.231)	(0.154)	(0.173)	(0.175)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use on staples = 1	0.406**	0.698***	0.651***						
	(0.194)	(0.198)	(0.208)						
Year FE	Yes	Yes	Yes						
Region FE	No	Yes	No						
Region*year FE	No	No	Yes						
Uganda									
Pesticide use on staples = 1	0.727***	0.574***	0.594***	0.538***	0.264*	0.263*	0.634***	0.375**	0.378**
	(0.223)	(0.171)	(0.150)	(0.168)	(0.151)	(0.152)	(0.194)	(0.162)	(0.154)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. All values specified in natural log terms. No other controls used in regressions.

Table A.13: Other short run human health indicators – with income control variable (household level)

	Any work day lost due to sickness (=1)			Recently fell sick (=1)			Recently visited a health worker (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1	0.0324	0.0395*	0.0435**	0.0247	0.0298	0.0331	0.00488	0.000316	0.00267
	(0.0203)	(0.0210)	(0.0208)	(0.0199)	(0.0207)	(0.0206)	(0.0194)	(0.0201)	(0.0201)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Nigeria									
Pesticide use = 1	0.0500***	0.0307*	0.0320*	0.0331*	0.0318	0.0321	0.0388**	0.0240	0.0273
	(0.0163)	(0.0180)	(0.0180)	(0.0177)	(0.0198)	(0.0201)	(0.0167)	(0.0188)	(0.0186)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1							0.0489**	0.0613***	0.0600***
							(0.0190)	(0.0192)	(0.0193)
Year FE							Yes	Yes	Yes
Region FE							No	Yes	No
Region*year FE							No	No	Yes
Uganda									
Pesticide use = 1	0.0834**	0.0558	0.0546	0.0731***	0.0471*	0.0354	0.118***	0.0966***	0.0862***
	(0.0385)	(0.0362)	(0.0350)	(0.0282)	(0.0275)	(0.0277)	(0.0293)	(0.0285)	(0.0292)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions. All estimated via OLS. No income control variable is available for Ethiopia, so the consumption aggregate is used as a proxy.

Table A.14: Other short run human health indicators – by pesticide type (household level)

	Any work day lost due to sickness (=1)			Recently fell sick (=1)			Recently visited a health worker (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Herbicide = 1	0.0531**	0.0614***	0.0601***	0.0413**	0.0461**	0.0452**	0.0386*	0.0255	0.0244
	(0.0208)	(0.0216)	(0.0216)	(0.0201)	(0.0210)	(0.0210)	(0.0202)	(0.0209)	(0.0209)
Other pesticide = 1	-0.0468	-0.0427	-0.0345	-0.0504	-0.0467	-0.0401	-0.0132	-0.0195	-0.0147
	(0.0311)	(0.0311)	(0.0310)	(0.0312)	(0.0312)	(0.0311)	(0.0301)	(0.0299)	(0.0300)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Nigeria									
Herbicide use = 1	0.0664***	0.0305	0.0313	0.0337*	0.0448**	0.0459**	0.0309*	0.0108	0.00791
	(0.0163)	(0.0193)	(0.0194)	(0.0176)	(0.0209)	(0.0212)	(0.0168)	(0.0198)	(0.0197)
Other pesticide = 1	-0.0174	0.00749	0.00559	0.00872	0.0269	0.0255	0.0213	0.0273	0.0327*
	(0.0181)	(0.0184)	(0.0185)	(0.0200)	(0.0210)	(0.0209)	(0.0181)	(0.0191)	(0.0191)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Table A.15: Other short run human health indicators – by pesticide type with income control variable (household level)

	Any work day lost due to sickness (=1)			Recently fell sick (=1)			Recently visited a health worker (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Herbicide = 1	0.0495**	0.0583***	0.0571***	0.0370*	0.0428**	0.0420**	0.00683	0.00327	0.00233
	(0.0209)	(0.0217)	(0.0217)	(0.0203)	(0.0211)	(0.0212)	(0.0201)	(0.0208)	(0.0209)
Other pesticide = 1	-0.0511	-0.0466	-0.0383	-0.0548*	-0.0505	-0.0438	-0.0356	-0.0385	-0.0339
	(0.0312)	(0.0313)	(0.0311)	(0.0314)	(0.0314)	(0.0312)	(0.0301)	(0.0299)	(0.0300)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Nigeria									
Herbicide use = 1	0.0666***	0.0251	0.0221	0.0383**	0.0334	0.0313	0.0342*	0.00124	-0.00438
	(0.0179)	(0.0211)	(0.0212)	(0.0192)	(0.0227)	(0.0232)	(0.0184)	(0.0217)	(0.0215)
Other pesticide = 1	0.000753	0.0320	0.0335*	0.0351	0.0460**	0.0456**	0.0369*	0.0440**	0.0502**
	(0.0201)	(0.0202)	(0.0200)	(0.0221)	(0.0232)	(0.0232)	(0.0202)	(0.0213)	(0.0212)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes

No income control variable is available for Ethiopia, so the consumption aggregate is used as a proxy.

Table A.16: Other short run human health indicators – on staples (household level)

	Any work day lost due to sickness (=1)			Recently fell sick (=1)			Recently visited a health worker (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ethiopia									
Pesticide use = 1	0.0492**	0.0554***	0.0561***	0.0418**	0.0454**	0.0460**	0.0368*	0.0250	0.0249
	(0.0202)	(0.0209)	(0.0209)	(0.0196)	(0.0204)	(0.0204)	(0.0197)	(0.0203)	(0.0204)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Nigeria									
Pesticide use = 1	0.0392**	0.0159	0.0160	0.0347**	0.0348*	0.0366*	0.0372**	0.0278	0.0263
	(0.0163)	(0.0177)	(0.0178)	(0.0173)	(0.0194)	(0.0196)	(0.0164)	(0.0181)	(0.0180)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes	No	No	Yes
Tanzania									
Pesticide use = 1							0.127***	0.138***	0.108**
							(0.0407)	(0.0413)	(0.0434)
Year FE							Yes	Yes	Yes
Region FE							No	Yes	No
Region*year FE							No	No	Yes
Uganda									
Pesticide use = 1	0.0845**	0.0648*	0.0692*	0.0522*	0.0263	0.0239	0.103***	0.0830***	0.0865***
	(0.0368)	(0.0368)	(0.0371)	(0.0297)	(0.0303)	(0.0305)	(0.0302)	(0.0310)	(0.0319)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No	No	Yes	No
District*year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions. All estimated via OLS.