The unintended consequences of agricultural input intensification: Human health implications of agro-chemical use in Sub-Saharan Africa

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Abstract: While agro-chemicals, like pesticides, fungicides, and herbicides, are often promoted as inputs that increase agricultural productivity by limiting a range of nuisance pests that cause pre-harvest losses, their use may not be without negative human health and labor productivity implications. We explore the relationship between agro-chemical use and the value of crop output at the plot level and a range of human health outcomes at the household level using nationally representative panel survey data from four Sub-Saharan African countries where more than ten percent of main season cultivators use agro-chemicals. We find a positive gain in the value of harvest from using agro-chemicals, with similar magnitudes across three of the four countries under study, but also increases in costs associated with human illness, including increased health expenditures related to illness and time lost from work due to sickness in recent past. We motivate our empirical work with a simple dynamic optimization model that clearly shows the role that farmer understanding of these feedbacks can play in optimizing the use of agro-chemicals, which underscores the role of agricultural and public health extension as modern input intensification proceeds in the region.

JEL codes: I15, I31, J28, J32, 013, O33, Q12

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1. Introduction

Modern agricultural inputs—like inorganic fertilizer and agro-chemicals—have the potential to help farmers boost productivity significantly, a goal critical to structural transformation and poverty reduction, particularly in regions like Sub-Saharan Africa (SSA). Recent panel data analysis, for example, 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). While this link has long been well-theorized in the agricultural development literature (Johnson, Hazell, Gulati 2003; Johnston and Mellor 1961; Schultz 1964), this new empirical evidence elevates the importance of focusing on the drivers of agricultural productivity growth as a prerequisite for structural change in SSA and elsewhere.

But the use of modern agricultural inputs may not be without risks of negatively affecting human health or the surrounding environment, thereby decreasing net growth in productivity and well-being in the short and/or longer run. These unintended consequences may be most true of agro-chemicals—like pesticides, fungicides, and herbicides—and especially when over-applied, used without appropriate precautions and protective equipment, or when the chemicals available in the market are dangerous ones.

At least some of these conditions are found in pockets of SSA. For instance, 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 informal and unlicensed dealers. It is also well-acknowledged that agro-chemicals can be destructive to agricultural land, waterways, biodiversity, and beneficial predators (Fenner et al. 2013; Racke 2003; van der Werf 1996) which, in turn, can also contribute to the deterioration of human health and productivity outcomes.

These potentially opposing effects of agro-chemical use—enhancing agricultural productivity while diminishing human health and/or 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 modern agricultural inputs; trade-offs abound. Indeed, the agricultural productivity gains may be nullified entirely where there are major indirect costs associated with applying these agro-chemicals. Even when these costs are directly borne by producers, farmers may continue to use pesticides due to 'lock in' effects (Wilson and Tisdell 2001). 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 African contexts, but always with very limited sample sizes specific to particular cropping patterns (generally cotton and rice) and in areas where agro-chemical use is known to be high (Ajayi and Waibel 2003; 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 productivity and health impacts of agro-chemicals use in developing country agriculture.

Recent descriptive evidence shows that agricultural households across SSA apply pesticides, fungicides, and herbicides 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 agro-chemical, ranging from 3 percent in Malawi to 33 percent in Nigeria. Moreover, unlike the widespread perception that agro-chemical use is confined to cash crops, especially cotton, Sheahan and Barrett (2014) find agro-chemical use is similar across plots planted in a range of crops, including staple grains, and with geographic breadth not 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 link between the use of agro-chemicals in crop agriculture and both agricultural productivity and farmer-reported health outcomes and health care costs. Given that SSA farmers appear to be using agro-chemicals 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 seems overdue. We motivate our analysis by presenting a simple but instructive model that explores the role of information, especially as related to the feedback of agro-chemical use on human health impacts over time, in identifying the optimal application levels. The intuitive point of the model is to highlight the likelihood that farmers who fail to appreciate the effects of agro-chemicals on health—or means by which one might mitigate those effects—are likely to over-apply these inputs.

While the data employed in this analysis do not include the detailed information about chemical types and verified ailments—as in more spatially focused studies such as Antle and Pingali (1994)—this paper is the first to link agro-chemical use with both its crop productivity benefits and human health costs across nationally representative data spanning multiple countries and cropping systems in SSA. Although still not exhaustive of the potential set of costs, notably any of those related to the ambient environment, such analysis is important to guide tailored policies that would target not only the use of more inputs, but also the safer and more appropriate use of those inputs. Our results suggest both positive harvest value effects and negative human health implications and costs associated with agro-chemical use in the four countries we study where at least ten percent of main season cultivators use agro-chemicals on their farms.

2. Mechanisms

While our analysis does not enable us to establish through which mechanisms agro-chemical use affects human health outcomes and related costs, the following two sub-sections detail these potential avenues as a means of motivating both our model and the empirical analysis that is our main contribution.

2.1. Positive impacts of agro-chemicals on human health

Before unpacking the ways in which agro-chemicals 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 and insecticides reduces the incidence of the pests and insects, respectively, that can severely limit yields and 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. Moreover, 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 agro-chemical 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, procuring medicines, purchasing and using a mosquito net to prevent malaria, etc.). Similarly, if these agro-chemicals are labor-saving technologies and relatively less expensive, then farmers benefit from increased profits not only from increased revenues but also from reduced costs of other agricultural inputs.

Cooper and Dobson (2007) also point out that it is not only the farming households using pesticides or other agro-chemicals that benefit. 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. A 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 agro-chemical use are considerable.

2.2. Negative impacts of agro-chemicals on human health

But with these gains comes the potential for real costs. Agro-chemicals are often toxic to humans, as is well documented in the toxicology literature (Hayes 1991). Occupational pesticide exposure can have minor to acute negative neurological, respiratory, immunologic, and reproductive effects, and the use of certain types of agro-chemicals is positively related to diagnoses of cancer (Weisenburger 1993). Research also shows that pesticides, especially, can damage human immune systems, increasing the incidence of sickness over time (Culliney, Pimentel, Pimentel 1992).

Potentially 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. Not only at the time of application, but 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; Mekonnen and Agonafir 2002; Stadlinger *et al.* 2011).

Non-agricultural laborer members of a farm household with agro-chemical application are also likely to come into contact with these agro-chemicals. Where agricultural fields are located near household dwellings, other household members – particularly children – are likely to walk through or play in fields with chemical treatment. The storage of chemicals, especially in previously opened container, in close proximity to where household members congregate, eat, or sleep is another potential 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 their accumulation in common dust. Pesticide residues can also be consumed directly from produce skins.

Furthermore, rural agricultural households with limited resources often reuse agro-chemical containers. Where residues are not entirely cleaned from the 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 agro-chemical residues is high. Williamson (2003) notes that over three-quarters of all agro-chemical 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 agro-chemicals can also pollute the environment from which rural households critically depend and derive livelihoods which can indirectly affect human health. Agro-chemicals 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. Agro-chemicals can also cause long term damage to 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 a high degree of pesticide dissipation into and accumulation in soils (Rosendahl *et al.* 2008). Taken together, the potential for significant costs related to agro-chemical use, particularly misuse and haphazard disposal, are also known to be high.

3. Model

Given both the positive and negative expected outcomes associated with agro-chemical use on farm, critical questions arise around farmers' understanding of these benefits and costs. In particular, the gains may be relatively evident—fewer pests and weeds, less human labor requirements, etc.—but the costs may be less obviously attributable to agro-chemical use. To better understand how information about the adverse human health impacts of agro-chemical use might affect a farmer's choice of optimal application levels, we offer a simple dynamic optimization model of agro-chemicals use with current and/or dynamic feedback on human health.[1] 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). On the contrary, in cotton producing areas of Cote d'Ivoire, Ajayi and Akinnifesi (2007) found that half of their purposively drawn sample of farmers understood the 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 agro-chemicals use levels or conditions, or might be somehow bounded away from compliance with those limits.

Consider a model in which a profit maximizing farming household makes its choice of optimal agro-chemical usage at time *t* conditional on agricultural production levels as well as prospective current and/or persistent household labor shocks derived from worker related illness. We abstract away from uncertainty in production and health effects, as well as from frictions that might make profit maximization an inaccurate proxy for the household's objective function so as to keep the model simple and the mechanisms clear for the purposes of drawing out the intuition. The model takes the following form:

$$L = \max_{c_t, v_t} \pi = \sum_{t=0}^{\infty} \rho^t [f(v_t, c_t | H_t) - r \cdot v_t - p \cdot c_t - w \cdot H_t - d \cdot I(c_t) \tag{1}$$

[1] The only other economic model related to agro-chemical use we are aware of is one offered by Waterfield and Zilberman (2012) who, more specifically, study the design of optimal government policy options for pest management where private optimal decisions diverge significantly from socially optimal management strategies.

$$\text{s.t. } H_{t+1} - H_t = g(H_t, c_t) \text{ and } \underline{H} > 0$$

where $\rho \,\epsilon[0,1]$ is the intertemporal discount rate, *f* is the agricultural production function that maps choice variable inputs, including composite variable factors of production v_t (like land and fertilizer) as well as agro-chemical inputs c_t and the quasi-fixed health-adjusted stock of labor H_t, into crop yield output. The prices of each of these inputs are represented by *r*, *p*, and *w*, respectively, all measured relative to the composite product price, which serves as the numéraire. We make the standard assumptions that $f(\cdot)$ is monotonically increasing at a decreasing rate (i.e. $f'(\cdot) > 0$, $f"(\cdot) < 0$), indicating diminishing returns to the use of agro-chemicals and other inputs.

In addition to these standard components of a profit function, $I(c_t)$ is an indicator variable that represents contemporaneous adverse human health effects that are triggered if and only if agro-chemical application surpasses a threshold level of safe exposure, $\hat{c}$, above which agro-chemical use results in significant, visible, adverse human health effects requiring some curative treatment. The variable d represents the present period costs of addressing ill health induced by agro-chemical use in excess of $\hat{c}$. These costs may include visits to health workers, drugs, etc.

This threshold level of safe agro-chemicals exposure, $\hat{c}$, also appears in the piecewise state equation $g(\cdot)$ that describes the impacts of current period use of agro-chemicals on the health-adjusted stock of labor in the next period H_{t+1}:

$$H_{t+1} \equiv g(H_t, c_t) = (1 - a(c_t))H_t \tag{2}$$
$$a(c_t) = 0 \; if \, c_t \leq \hat{c}, \gamma c_t \; if \; c_t > \hat{c}$$

where the health degradation parameter, $\gamma > 0$, $\hat{c} > 0$, and $\frac{\partial g(\cdot)}{\partial c_t} \leq 0$, which implies that $\frac{\partial a(\cdot)}{\partial c_t} \geq 0$ and $a(\cdot) \in [0,1]$ under the mild assumptions that H_{t+1} cannot be negative and household composition is fixed, thus the stock of labor cannot grow.

The optimal agro-chemical input level ${c_t}^*$ is found by evaluating the current value Hamiltonian, incorporating the state equation that describes farmer health and λ_{t+1}, the shadow price for labor supply in period *t+1*. The current value Hamiltonian is as follows:

$$Y_t \equiv f(v_t, H_t, c_t) - r \cdot v_t - p \cdot c_t - w \cdot H_t - d \cdot I(c_t) + \rho\lambda_{t+1} g(H_t, c_t) \tag{3}$$

The first order conditions of Y_t with respect to agro-chemical use (c_t) and other variable inputs (v_t) are:

$$\frac{\partial Y}{\partial c_t} = \frac{\partial f(\cdot)}{\partial c_t} - p - d \cdot I_c(\cdot) + \rho\lambda_{t+1} \partial g(\cdot)/\partial c_t = 0 \tag{4}$$
$$\frac{\partial Y}{\partial v_t} = \frac{\partial f(\cdot)}{\partial v_t} - r = 0$$

which imply optimal input application rates follow the relations:

$$\frac{\partial f(\cdot)}{\partial v_t} = r \tag{5}$$

$$\frac{\partial f(\cdot)}{\partial c_t} = p + d \cdot I_c(\cdot) - \rho\lambda_{t+1} \cdot \frac{\partial g(\cdot)}{\partial c_t}$$

Because $\frac{\partial f(\cdot)}{\partial c_t} \geq 0$ and $\frac{\partial g(\cdot)}{\partial c_t} \leq 0$, increasing c_t improves current period agricultural productivity but may hurt future productivity by harming human health, inducing a trade-off. Since the derivative of the Hamiltonian with respect to c_t depends on both the production and health function derivatives with respect to c_t, the optimal rate of agro-chemical application (${c_t}^*$) for the farmer is the highest rate of application at which the future, discounted deterioration of laborer health does not outweigh the current marginal productivity gains on the farm.

The key to understanding the change in health-adjusted labor stock, the state variable, between two periods, is the discounted shadow value of labor. The shadow price λ_{t+1} determines the strength of the feedback the farmer perceives from the change in health due to agro-chemical use, given by $\frac{\partial g(\cdot)}{\partial c_t} \leq 0$. A higher shadow price magnifies the feedback from future adverse health effects. Thus, the farmer's ${c_t}^*$ depends both on the rates at which c_t directly affects farm productivity, $\frac{\partial f(\cdot)}{\partial c_t}$, and indirectly affects productivity through induced changes in current period health care expenditures, $d \cdot I_c(\cdot)$, and health-adjusted future labor stock, $\frac{\partial g(\cdot)}{\partial c_t}$, and also on the farmer's discounted shadow price or marginal value of health for the next period, $\rho\lambda_{t+1}$.

This is where information becomes important, even in this highly stylized example. If the farmer is completely unaware of the prospective adverse health effects from agro-chemical use or otherwise ignores them when making decisions about agro-chemical use, which is equivalent in this model to setting $\hat{c} = \infty$, then it follows from the assumptions made about $I_c(\cdot)$ and $g(H_t, c_t)$ that the farmer's optimal input level is necessarily higher than if she accounts for those costs directly. If $\hat{c} = \infty$ then the first order conditions reduce to:

$$\frac{\partial L}{\partial c_t} = f_c(\cdot) - p = 0 \tag{6}$$

$$\frac{\partial L}{\partial v_t} = f_v(\cdot) - r = 0$$

and agro-chemicals are treated just like any other input, applied up to the point where the current marginal revenue product equals the cost of the input. If the true $\hat{c} < \infty$, then the information gap reflected in farmer over-estimate of the safe threshold application rate for agro-chemicals—in this limiting case, falsely believing there is no such threshold—results in over-application, choosing a knowledgeconstrained application rate that is higher than the optimum chosen by a fully-informed farmer, $c_{kt}^{*} > c_t{}^{*}$. This can negatively impact both health and total production over time.[2]

Although one cannot precisely estimate the relevant optima without knowing the functional forms of $f(\cdot)$ and $g(\cdot)$, a test of the three hypotheses that underpin the analytical results—that agro-chemical use increases crop output, increases health care expenditures, and decreases labor availability, respectively—can serve as an illuminating substitute:

$$H_0: \frac{\partial f(\cdot)}{\partial c_t} = 0 \text{ vs. } H_A: \frac{\partial f(\cdot)}{\partial c_t} > 0 \tag{7}$$

$$H_0: \frac{\partial dI(\cdot)}{\partial c_t} = 0 \text{ vs. } H_A: \frac{\partial dI(\cdot)}{\partial c_t} > 0 \tag{8}$$

$$H_0: \frac{\partial g(\cdot)}{\partial c_t} = 0 \text{ vs. } H_A: \frac{\partial g(\cdot)}{\partial c_t} < 0 \tag{9}$$

Rejection of each of these nulls in favor of the one-tailed alternate hypotheses would indicate that this is a subject worthy of concern and further exploration. That is the task of our empirical exercise, as described below. Given the potential for negative health implications for non-farm working individuals in close proximity to chemicals as well as the possibility of indirect health benefits accrued through household-level income gains associated with productivity gains, we prefer to investigate these effects on a fuller set of individuals living in households where agro-chemicals are known to be present.

4. 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 agro-chemical-using households is the highest (Ethiopia, Nigeria, Tanzania, Uganda), as described in more detail by Sheahan and Barrett (2014).[3] More specifically, we utilize two waves of the 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,

[2] At the same time, receiving information that perpetuates false knowledge about the relationship between agro-chemical use and health outcomes may reduce true awareness and necessitate stronger negative self-feedback from agro-chemicals in order for the farmer to overcome incorrect information and recognize his/her illness or reduced labor productivity as described by $I_c(\cdot)$, and $g(H_t, c_t)$. Thus, though not explicitly stated, the quality and accuracy of information imparted, upon which characteristics of the model and therefore and its outcome $c^*$are likely dependent. Such external influences may either help or hinder the farmer to choose the true optimal level $c_t{}^*$.

[3] Sheahan and Barrett (2014) find that of their sample of main season cultivating households, 30.5 percent use agro-chemicals 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 with at least ten percent of households applying one of these chemicals in the main growing season in these particular cross-sections since the absence of adequate variation in agro-chemicals use in the other two countries makes analysis of those data essentially infeasible for our research question.

and 2012/13), and three waves of the Uganda National Panel Survey (2009/10, 2010/11, and 2011/12).[4] 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,[5] 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 where households move in to and out of cultivation. We apply the household sampling weights in all analysis, including with models specified at the plot level.[6] Table 1 provides more details on the sample size used in our analysis.

In each of these data sets, we observe the use of agro-chemicals at the plot level.[7] In some countries these data include all agro-chemical types lumped into one question, but in others we observe agro-chemicals applied by category (e.g., pesticides, herbicides, fungicides).[8] In no case do we observe further detail on chemical type (e.g., DDT, endosulfan, malathion), as is more common in studies with very narrow geographic focus.[9] Moreover, continuous application rates of agro-chemicals observed in the data (where available) are known to be a mix of diluted and concentrate volumes and weights, rendering the continuous measures incomparable even within a country or data set. Plot level agro-chemical use is therefore most reliably analyzed as a binary variable in these data sets. Figures 1-4 describe the prevalence of agro-chemical use when aggregating across agricultural plots to the household level for one cross-section of data in each of the four sampled countries.

In the household modules, several questions related to health are asked of all household members. Most uniformly across countries, the basic health status of individuals is recorded. These questions are not specific to agro-chemical 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.[10] In most countries, we also observe if individuals visited a health worker in the recent past and/or missed work or other usual activities on account of sickness. The

[4] All data sets are nationally representative except for Ethiopia 2011/12 which is representative of rural areas only.
[5] In Tanzania and Uganda, we also include households that "split" from a "parent" at some point during the panel.
[6] We use the weights provided in the first wave of the survey in all countries except Nigeria were a "panel weight" is provided with the data.
[7] While we use the term "plots" throughout our text, the parcel level was chosen in Uganda.
[8] We observe use of pesticides, herbicides, and fungicides separately in Ethiopia; pesticides and herbicides in Nigeria; then a lump sum of all agro-chemicals in Tanzania and Uganda (alongside a categorical variable for the "most important type").
[9] 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.
[10] 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 agro-chemical exposure or poisoning because we cannot expect individuals to accurately self-diagnose.

two variables for which we can more 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[11]).

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).[12] 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 actual 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 more exact 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.[13] For all countries where the data span two years, we use the first year as the reference point.

5. Estimation methods

The following two sub-sections described the panel data methods used to estimate the conceptual relationships that follow from the model described in Section 3. For any number of reasons, our strategy makes no attempt to identify causal associations between agro-chemical use, crop productivity, and human health outcomes; this is simply infeasible in these data. Instead, our aim remains to uncover correlations and relationships between these potentially related variables.

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[11] 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.

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

[13] These exchange rates can be found here: 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.

5.1. *Crop productivity outcomes associated with agro-chemical use*

In order to test the hypothesis in (7), we specify a simple linear 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:

$$y_{jkgt} = \beta_0 + \beta_1 c_{jkgt} + \boldsymbol{\gamma v_{jkgt}} + \tau_t + \varphi_{gt} + \omega_{kg} + \varepsilon_{jkgt} \tag{10}$$

where y is the value of all harvest at the plot level (inclusive of all crops), c is the binary agro-chemical 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 only have one cross-section of Ethiopia data for which we are able to value crop output, we adjust our control variables and fixed effects strategies for it accordingly. We specify y in both linear and log terms. Our coefficient estimate $\hat{\beta}_1$ describes the crop productivity gains associated with agro-chemical use, the hypothesis of interest in (7).

5.2. *Human health outcomes and costs associated with agro-chemical use*

To explore the relationship between agro-chemical use and a range of human health outcomes $\boldsymbol{h}$ at the household level k, we estimate a number of models derived from the following form:

$$\boldsymbol{h_{kgt}} = \rho_0 + \rho_1 c_{kgt} + \theta_t + \mu_{gt} + \epsilon_{kgt} \tag{11}$$

From the set of health outcomes available in the LSMS-ISA data sets under consideration, $\boldsymbol{h}$ 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 where someone in the household fell sick in the recent past, a binary variable to describe where an individual in the household recently visited a health worker due to illness or sickness, and a binary variable where a member of the household 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 agro-chemical 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

[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.

describes where agro-chemicals are used on any plot within a household's farm and h is an aggregation across household members.

Similar to model (10), 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, 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 agro-chemical 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. 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 agro-chemical use on farm. When the dependent variable is the value of health expenditures related to recent illness, this serves as a test of hypothesis (8). For the dependent variables time lost from work, falling sick in the recent past, or suffering chronic illness, we have a test of hypothesis (9). The coefficient estimate $\hat{\rho}_1$ could be interpreted as a test of either (8) or (9) when the dependent variable is visit to a health worker.

6. Results

6.1. Crop productivity outcomes

Table 3 presents partial results of estimating equation (10) under a number of specifications (with full regression output for each country in the Appendix). In all four countries, we find that agro-chemical use is associated with positive and statistically significant increases in the value of harvest on a given plot. In Ethiopia, plots with agro-chemicals have harvest values 19-32 USD more than plots without agro-chemicals; 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 agro-chemical 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 agro-chemicals 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 suggest that there are, indeed, strongly positive and relatively large crop productivity gains associated with using agro-chemicals on farm. These results hold when using a full suite of controls variables, including crop-type fixed effects (except in Nigeria) which should control for the fact that crops with higher market values may receive agro-chemicals more frequently than lower value staples. We emphasize that these are not production function estimates and prospective endogeneity precludes any causal inference. Nonetheless, the sizable, consistent, positive partial correlation estimates strongly suggest agricultural productivity gains associated with agro-chemical use.

6.2. Human health outcomes

The remaining tables display the results of estimating various versions of equation (11). Table 4 presents the relationship between the value of health expenditures on account of illness and sickness (e.g., curative work and treatments) and the use of agro-chemicals at the household level. In the three countries for which we are able to study this value (Nigeria, Tanzania, Uganda), all are specific to costs incurred over the last month; however, in Nigeria, these costs are only associated with the first consultation and, therefore, may be less than the full cost where the household incurred additional expenses beyond one visit to a health care provider (see Table A.1 in the Appendix). In both the OLS and Tobit specifications, we observe positive and significant relationships between agro-chemical use and household health expenditures in Tanzania and Uganda. In Nigeria, the statistically significant effects only emerge in the Tobit specifications, likely because 74 percent of household observations are zero values (relative to 28 in Tanzania and 34 in Uganda). In the Tobit specification with the most additional control variables (column 6), these effects are very similar in magnitude for Tanzania and Uganda.

Table 5 displays the results related to our other value measure: the value of time lost from work due to illness or sickness. 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 estimated effects are only positive and statistically significant (at the 10 percent level) in the Tobit regressions with most controls. In Nigeria, statistically significant effects emerge in only one specification. In Uganda, we observe three specifications with positive and statistically significant effects.

Out of concern that differences in local wage levels may abstract from these value-specific effects, we also present the number of days lost from work (not the value of time lost) in Table 6. 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 slight differences in the recall period of the underlying questions asked of respondents: one month in Nigeria and Uganda while two months in Ethiopia (see Table A.1 in the Appendix). When standardizing even further, transforming this continuous measure into a binary one representing *any* days missed from work over the relevant time frame, Table 7 displays positive and statistically significant estimated relationships across most specifications between time lost from work or other usual activities and the use of agro-chemicals on farm. Together, these results suggest that households that use agro-chemicals are indeed more likely than those that do not to lose some work time and potential income as a result of illness and sickness.

While it may be tempting to directly compare these two health-related value measures we provide (costs) with the additional value of harvest on account of agro-chemical use on farm (benefits), these values are not directly comparable because (i) the harvest value estimates are specified at the plot level while health outcomes are specified at the household level and (ii) the magnitude of these values (not the percent changes) would be more instructive for providing a proper cost-benefit analysis. Moreover, neither of these values necessarily encompasses all potential health related costs, particularly where the negative effects may accrue over the longer term and, most extremely, result in premature death. For example, in their sample of smallholder vegetable farmers in Tanzania, Ngowi *et al.* (2007) find far more farmers reporting 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 agro-chemical related monetary losses.

With this in mind, we then move to health outcomes without monetary values attached to them. Table 8 shows the correlations between a household member falling sick in the recent past (two months for Ethiopia, one month for Nigeria and Uganda) and agro-chemical use. In Ethiopia and Nigeria, our preferred specification (column 3) 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 agro-chemicals 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 agro-chemicals use, as it is unrelated to access to medical facilities and/or the ability to take time off of work, the trade-off being that there is no way to value and compare this response.

Table 9 explores the relationship between agro-chemical use and visiting a health worker. In the two countries for which we can isolate visits on account of actual illness over the last one 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 agro-chemical 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 10 attempts to convey the relationship between longer term or chronic sickness and household agro-chemical use. Because the agro-chemical use that we observe is contemporaneous and we know very little about the historic use of this or other inputs, we would not necessarily expect there to be a strong relationship unless agro-chemical use has been an enduring feature of farm management practices. Moreover, the measures we observe are imperfect ones. In Ethiopia, where we find no effects, we are only able to correlate the incidence of sickness that lasted more than three months in the last year, which is not necessarily inclusive of the types of chronic illnesses that may arise from agro-chemical poisoning. In Nigeria, where we find consistently positive and significant effects, the question from which we derive our variable is specific to visiting a health worker because of a long term or chronic illness, implying a subset of the cases from Table 9, not all chronic illness that may be present.

One important extension of our main analysis is breaking the agro-chemical aggregate variable into its constituent types where we can, in Ethiopia and Nigeria. We re-run all of our human health analysis specific to the types of agro-chemicals used: pesticide, herbicides, and fungicides in Ethiopia, and pesticides and herbicides in Nigeria. All of these tables can be found in the Appendix (Tables A.6 though A.11). In each case, we find that herbicide use accounts for all of the positive and statistically significant estimated relationships, often improving the precision of those estimated partial correlation coefficients as well. Recall from Table 2 that herbicide use makes up the bulk of reported agro-chemical application in both Ethiopia and Nigeria. This seems strong suggestive evidence that herbicides may be of particular concern among the broader array of agro-chemicals in use in SSA agriculture.

Once again we emphasize that we cannot establish a causal relationship with respect to any of these health-related estimates. But the consistent positive association is clear in the data and consistent with both prior evidence from elsewhere (Antle and Pingali 1994) and with the large toxicology literature. We offer further reflections in the discussion and conclusions section that follows.

7. Discussion and conclusions

Using nationally representative panel household survey data from four countries in Sub-Saharan Africa—Ethiopia, Nigeria, Tanzania, and Uganda—with relatively high use of agro-chemicals, this paper explores the relationship between agro-chemical use on farmers' fields, the value of output conditional on agro-chemical application, and a suite of human health costs and status indicators. We find consistent evidence that agro-chemical use is associated with significantly greater agricultural output value, but also costly from the standpoint of a range of human health outcomes negatively associated with agro-chemical use. These results seem particularly profound given the national-level representativeness of our sample, inclusive of farming households across cropping systems and with access to a whole range of agro-chemicals. We expose, perhaps for the first time, that these negative effects are pervasive beyond just a small selection of crops, like the cotton and rice systems normally studied with small, non-representative samples. While we cannot interpret any of these regression estimates as causal, the consistency in our estimated correlations—across samples, specifications, and estimators as well as with intuition and theory—suggests that much more attention needs to be directed towards understanding the causal link and, where it truly exists, the extent to which it might be mitigated with better policies or programs to promote farmer awareness of the human health consequences of agro-chemical application rates. We cannot establish whether current use rates are too high, or perhaps sub-optimal. But our results are consistent with a stylized model in which trade-offs exist and information gaps for farmers would naturally lead to over-application of dangerous agro-chemicals.

In light of our empirical results, one might expect that (private or public) extension efforts to inform farmers about the potential negative human health effects of agro-chemical use could help promote optimal use of agro-chemicals. 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 agro-chemical use, particularly overuse, and doing so using participatory methods. At the same time, more judicious use of agro-chemicals 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 on which they depend 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 relationships as a call to other researchers to better understand the decision making and behavior that underlie our results using more tailored questionnaires 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 agro-chemicals on farm and/or stored within the family dwelling? Or, perhaps even worse, are they fully aware that household sickness is related to agro-chemical use but continue to apply despite the known costs?

From a human health perspective, even the very high incidence of reported sickness we uncover in these four countries, irrespective of agro-chemical use, is concerning. Structural transformation may be jump-started by agricultural productivity growth, but tending to an unhealthy population will also be essential for sustained agricultural and rural non-farm productivity growth and improved standards of living. Where agro-chemical use may undermine human health status, then 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. Forsaking the health, and thereby productivity, of the very individuals who will carry out the structural transformation still yet to truly unfold in rural Africa while promoting the use of yield-enhancing inputs may prove unwise.

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
Agro-chemical 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)
Pesticide use (binary)	0.09 (0.02)	0.10 (0.02)	0.19 (0.01)	0.20 (0.01)	-	-	-	-	-	-
Herbicide use (binary)	0.27 (0.03)	0.29 (0.03)	0.22 (0.01)	0.26 (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: Agro-chemical 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. Agro-chemical 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.

Table 3: Value of harvest/production on account of agro-chemical use (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			
Agro-chem 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			
Agro-chem 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			
Agro-chem 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			
Agro-chem 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 health expenditures on account of illness/sickness (household level)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	Left censored Tobit	Left censored Tobit	Left censored Tobit
Nigeria						
Agro-chemical use = 1	-0.0199	0.0368	0.0533	0.114	0.247**	0.275**
	(0.0343)	(0.0378)	(0.0374)	(0.110)	(0.125)	(0.125)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes
Tanzania						
Agro-chemical use = 1	0.293***	0.390***	0.388***	0.368***	0.511***	0.509***
	(0.0749)	(0.0754)	(0.0758)	(0.0949)	(0.0957)	(0.0960)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes
Uganda						
Agro-chemical use = 1	0.531***	0.433***	0.422***	0.763***	0.599***	0.576***
	(0.135)	(0.111)	(0.0956)	(0.186)	(0.142)	(0.128)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No
District*year FE	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 5: Value of lost work time from illness/sickness (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) Left censored Tobit	(5) Left censored Tobit	(6) Left censored Tobit
Ethiopia						
Agro-chemical use = 1	0.0659	0.107	0.122	0.211	0.284*	0.316*
	(0.0734)	(0.0777)	(0.0775)	(0.157)	(0.166)	(0.166)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes
Nigeria						
Agro-chemical use = 1	0.0860	0.00271	0.0139	0.398**	0.118	0.144
	(0.0545)	(0.0603)	(0.0616)	(0.188)	(0.215)	(0.217)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes
Uganda						
Agro-chemical use = 1	0.389***	0.169	0.147	0.510***	0.244*	0.215
	(0.145)	(0.103)	(0.102)	(0.183)	(0.136)	(0.135)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No
District*year FE	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 6: Number of days lost from work due to illness/sickness (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) Left censored Tobit	(5) Left censored Tobit	(6) Left censored Tobit
Ethiopia						
Agro-chemical use = 1	0.0584	0.0658	0.0762	0.174	0.201	0.225*
	(0.0591)	(0.0626)	(0.0625)	(0.125)	(0.133)	(0.132)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
State*year FE	No	No	Yes	No	No	Yes
Nigeria						
Agro-chemical use = 1	0.0714**	0.0114	0.0159	0.277**	0.0890	0.100
	(0.0346)	(0.0390)	(0.0398)	(0.118)	(0.136)	(0.137)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	Yes	No
Region*year FE	No	No	Yes	No	No	Yes
Uganda						
Agro-chemical use = 1	0.297**	0.187*	0.151	0.366***	0.228**	0.181
	(0.120)	(0.0990)	(0.0965)	(0.138)	(0.115)	(0.113)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	No	Yes	No
District*year FE	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.

Table 7: Any days lost from work due to illness/sickness, binary (household level)

	(1) OLS	(2) OLS	(3) OLS
Ethiopia			
Agro-chemical use = 1	0.0367*	0.0431**	0.0468**
	(0.0201)	(0.0208)	(0.0207)
Year FE	Yes	Yes	Yes
State FE	No	Yes	No
State*year FE	No	No	Yes
Nigeria			
Agro-chemical use = 1	0.0382***	0.0183	0.0191
	(0.0148)	(0.0166)	(0.0168)
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Region*year FE	No	No	Yes
Uganda			
Agro-chemical use = 1	0.0886**	0.0637*	0.0627*
	(0.0374)	(0.0351)	(0.0335)
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 8: Recently fell sick, binary (household level)

	(1) OLS	(2) OLS	(3) OLS
Ethiopia			
Agro-chemical use = 1	0.0294	0.0336	0.0367*
	(0.0196)	(0.0204)	(0.0204)
Year FE	Yes	Yes	Yes
State FE	No	Yes	No
State*year FE	No	No	Yes
Nigeria			
Agro-chemical use = 1	0.0210	0.0335*	0.0343*
	(0.0161)	(0.0182)	(0.0185)
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Region*year FE	No	No	Yes
Uganda			
Agro-chemical use = 1	0.0788***	0.0522**	0.0395
	(0.0275)	(0.0265)	(0.0263)
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 9: Recently visited a health worker, binary (household level)

	(1) OLS	(2) OLS	(3) OLS
Ethiopia			
Agro-chemical use = 1	0.0376*	0.0249	0.0271
	(0.0193)	(0.0200)	(0.0201)
Year FE	Yes	Yes	Yes
State FE	No	Yes	No
State*year FE	No	No	Yes
Nigeria			
Agro-chemical use = 1	0.0311**	0.0232	0.0263
	(0.0150)	(0.0171)	(0.0170)
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Region*year FE	No	No	Yes
Tanzania			
Agro-chemical 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			
Agro-chemical use = 1	0.128***	0.107***	0.0950***
	(0.0285)	(0.0274)	(0.0276)
Year FE	Yes	Yes	Yes
District FE	No	Yes	No
District*year FE	No	No	Yes

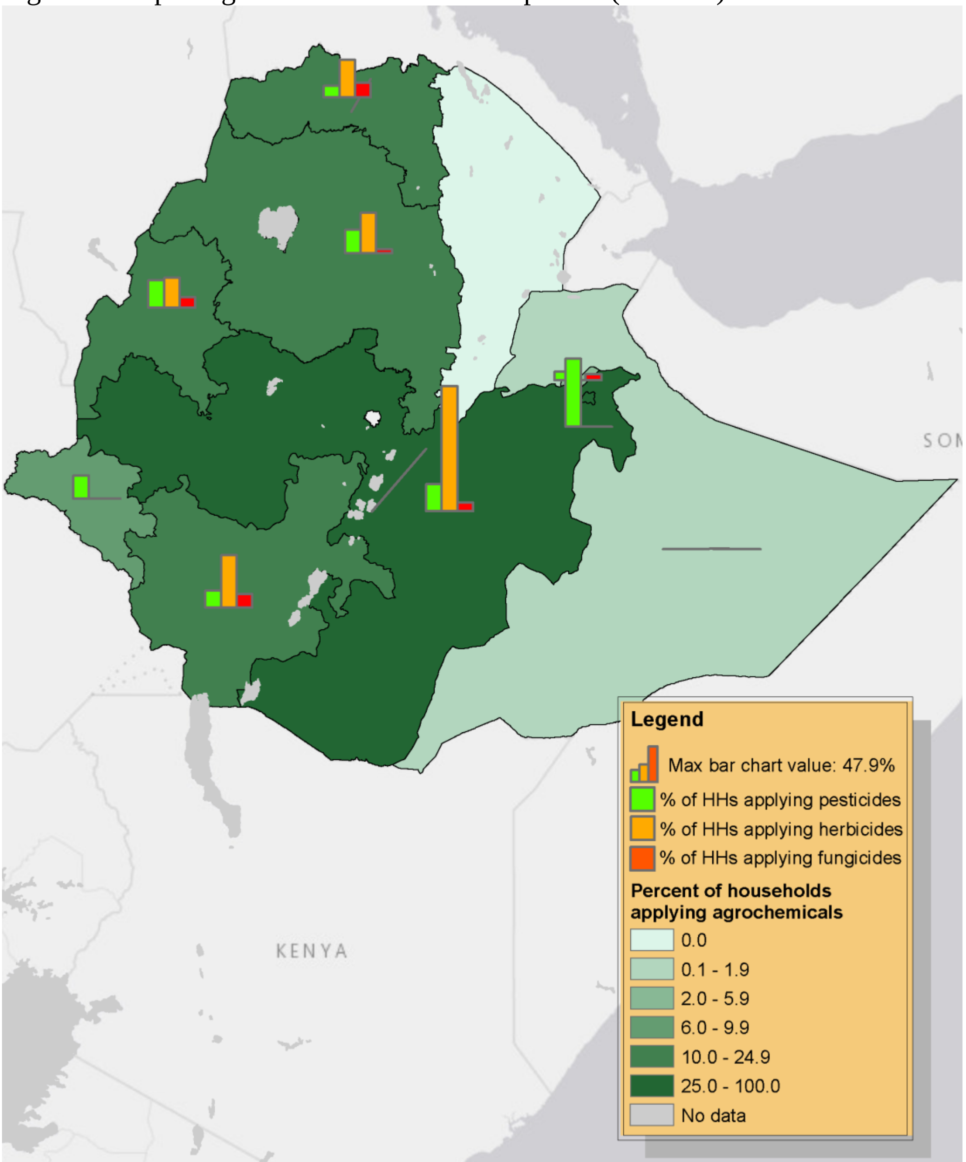
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions.

Table 10: Chronic or long term sickness in household, binary (household level)

	(1) OLS	(2) OLS	(3) OLS
Ethiopia			
Agro-chemical 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			
Agro-chemical 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

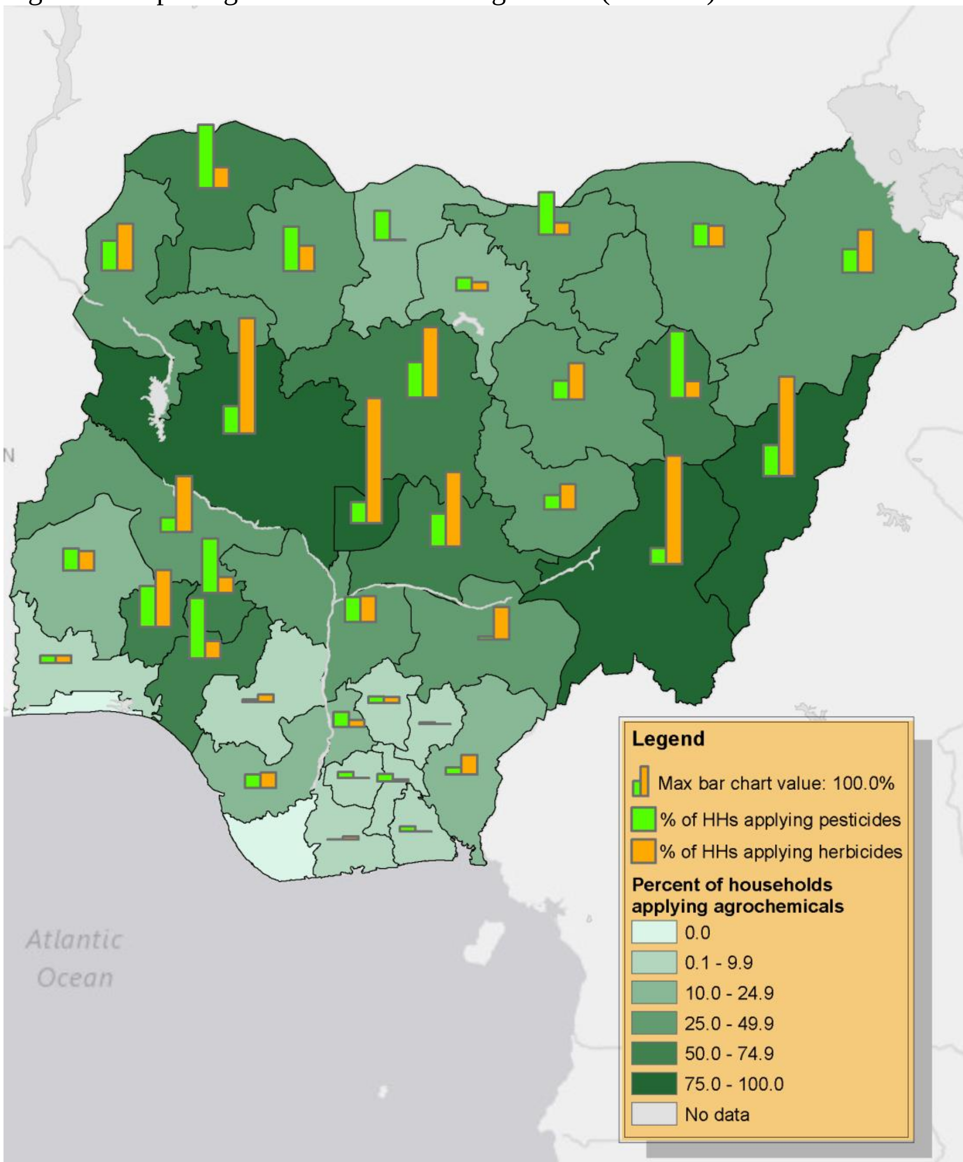
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in parenthesis) clustered at household level. No other controls used in regressions.

Figure 1. Map of agro-chemical use in Ethiopia Y1 (2011/12) cross section



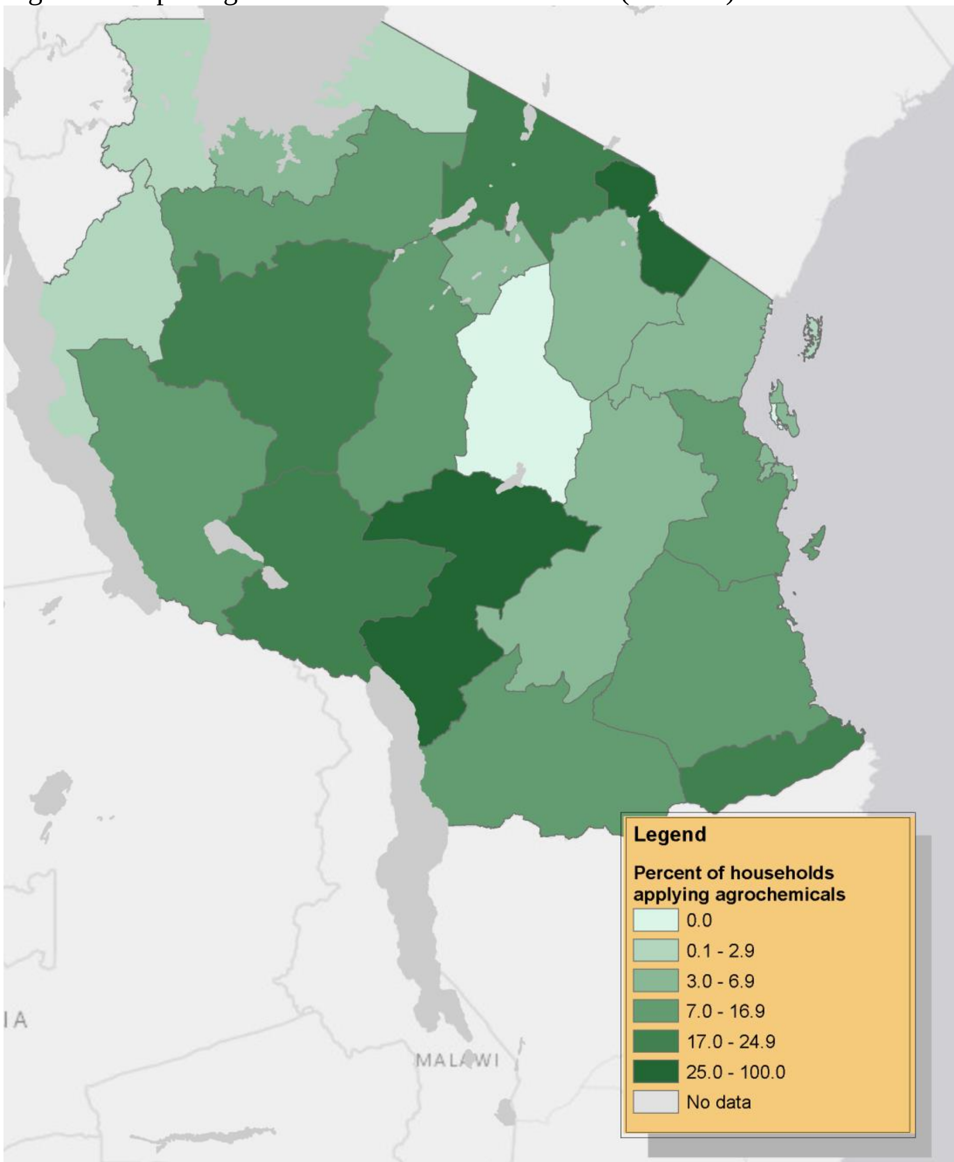
Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Ethiopia 2011/12.

Figure 2: Map of agro-chemical use in Nigeria Y1 (2010/11) cross section



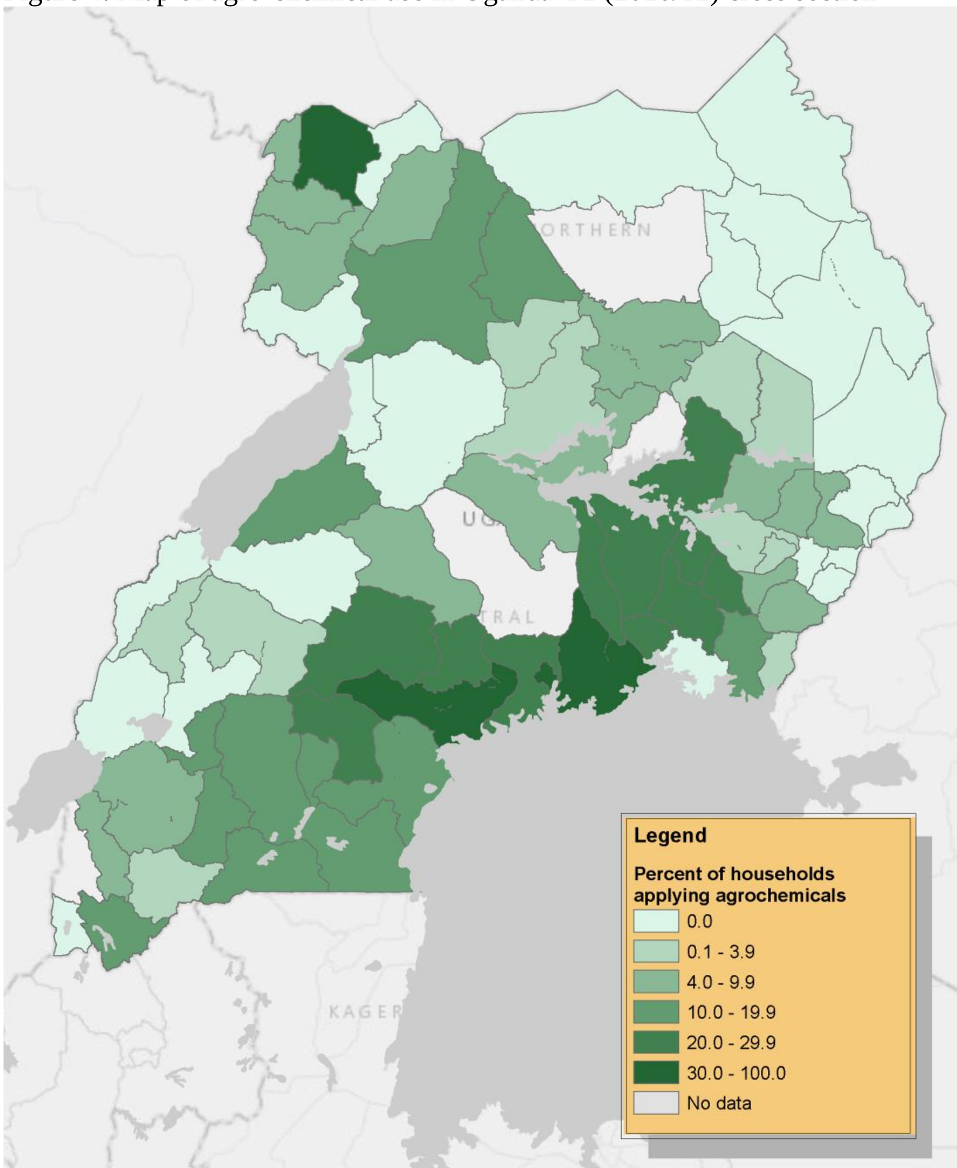
Source: Authors' calculations using the Living Standards Measurement Study Integrated Survey on Agriculture cross section for Nigeria 2010/11.

Figure 3: Map of agro-chemical 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 4: Map of agro-chemical 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.

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Appendix: Supplementary tables

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 harvest wage split by gender	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 by median harvest wage split by gender	N/A	Number of days lost from normal activities in last 30 days due to illness/injury, multiplied by median agricultural wage (aggregated across 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 production 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)
Agro-chemical 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 production 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)
Agro-chemical 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 production 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)
Agro-chemical 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 production 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)
Agro-chemical 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 lost work time from illness/sickness (household level)

	(1) Left censored Tobit	(2) Left censored Tobit	(3) Left censored Tobit	(4) Left censored Tobit	(5) Left censored Tobit	(6) Left censored Tobit	(7) Left censored Tobit	(8) Left censored Tobit	(9) Left censored Tobit
Ethiopia									
Pesticide use = 1	-0.346	-0.290	-0.205						
	(0.270)	(0.270)	(0.270)						
Herbicide use = 1				0.334**	0.420**	0.407**			
				(0.160)	(0.172)	(0.171)			
Fungicide use = 1							-0.280	-0.244	-0.359
							(0.384)	(0.384)	(0.384)
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	-0.325	0.0391	0.0113						
	(0.240)	(0.245)	(0.243)						
Herbicide use = 1				0.772***	0.277	0.305			
				(0.197)	(0.238)	(0.237)			
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.

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

	(1) Left censored Tobit	(2) Left censored Tobit	(3) Left censored Tobit	(4) Left censored Tobit	(5) Left censored Tobit	(6) Left censored Tobit	(7) Left censored Tobit	(8) Left censored Tobit	(9) Left censored Tobit
Ethiopia									
Pesticide use = 1	-0.0421	-0.0373	-0.0275						
	(0.0329)	(0.0329)	(0.0326)						
Herbicide use = 1				0.0531**	0.0614***	0.0601***			
				(0.0208)	(0.0216)	(0.0216)			
Fungicide use = 1							-0.0151	-0.0127	-0.0258
							(0.0487)	(0.0489)	(0.0488)
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	-0.325	0.0391	0.0113						
	(0.240)	(0.245)	(0.243)						
Herbicide use = 1				0.772***	0.277	0.305			
				(0.197)	(0.238)	(0.237)			
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.

Table A.8. Any days lost from work due to illness/sickness, binary (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
Ethiopia									
Pesticide use = 1	-0.0421	-0.0373	-0.0275						
	(0.0329)	(0.0329)	(0.0326)						
Herbicide use = 1				0.0531**	0.0614***	0.0601***			
				(0.0208)	(0.0216)	(0.0216)			
Fungicide use = 1							-0.0151	-0.0127	-0.0258
							(0.0487)	(0.0489)	(0.0488)
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	-0.0174	0.00749	0.00559						
	(0.0181)	(0.0184)	(0.0185)						
Herbicide use = 1				0.0664***	0.0305	0.0313			
				(0.0163)	(0.0193)	(0.0194)			
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. No other controls used in regressions.

Table A.9: Recently fell sick, binary (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
					Ethiopia				
Pesticide use = 1	-0.0483	-0.0439	-0.0360						
	(0.0332)	(0.0333)	(0.0331)						
Herbicide use = 1				0.0413**	0.0461**	0.0452**			
				(0.0201)	(0.0210)	(0.0210)			
Fungicide use = 1							-0.0236	-0.0212	-0.0320
							(0.0477)	(0.0475)	(0.0476)
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	0.00872	0.0269	0.0255						
	(0.0200)	(0.0210)	(0.0209)						
Herbicide use = 1				0.0337*	0.0448**	0.0459**			
				(0.0176)	(0.0209)	(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

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.10: Recently visited a health worker, binary (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
					Ethiopia				
Pesticide use = 1	-0.00336	-0.00704	-0.00164						
	(0.0321)	(0.0318)	(0.0318)						
Herbicide use = 1				0.0386*	0.0255	0.0244			
				(0.0202)	(0.0209)	(0.0209)			
Fungicide use = 1							0.0203	0.000886	-0.00811
							(0.0462)	(0.0460)	(0.0461)
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	0.0213	0.0273	0.0327*						
	(0.0181)	(0.0191)	(0.0191)						
Herbicide use = 1				0.0309*	0.0108	0.00791			
				(0.0168)	(0.0198)	(0.0197)			
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. No other controls used in regressions.

Table A.11: Chronic or long term sickness in household, binary (household level)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS
					Ethiopia				
Pesticide use = 1	0.0193	0.0206	0.0209						
	(0.0219)	(0.0220)	(0.0219)						
Herbicide use = 1				-0.0148	-0.0168	-0.0169			
				(0.0121)	(0.0130)	(0.0130)			
Fungicide use = 1							0.00592	0.00531	0.00484
							(0.0299)	(0.0302)	(0.0302)
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	0.0228**	0.0331***	0.0342***						
	(0.0112)	(0.0114)	(0.0116)						
Herbicide use = 1				0.0184*	0.00504	0.00777			
				(0.0104)	(0.0114)	(0.0116)			
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.. No other controls used in regressions.