Pesticide Handling and Human Health: Conventional and Organic Cotton Farming in Benin

by Ghislain B.D. Aihounton, Arne Henningsen, and Neda Trifkovic

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Ghislain B. D. Aïhounton[*,†], Arne Henningsen[‡], and Neda Trifkovic[§]

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Abstract

Synthetic pesticides can be detrimental to the health of humans, particularly when handled inappropriately, which is often the case in developing countries. We investigate to what extent using personal protective equipment (PPE) during pesticide application can mitigate the detrimental health effects of pesticides. Our empirical analysis is based on data from smallholder cotton farmers in Benin and includes both conventional cotton farmers who extensively use synthetic pesticides and organic cotton farmers who are only allowed to use bio-pesticides. Using per-capita health expenditure as proxy for the health of the farmers, our results show that conventional cotton farmers generally have significantly poorer health than organic cotton farmers because most conventional farmers wear insufficient PPE when spraying pesticides. While PPE use vastly improves the health of conventional farmers, we do not find a statistically significant effect on the health of organic cotton farmers, which could indicate that bio-pesticides have much smaller detrimental health effects than synthetic pesticides. However, conventional farmers have a similar state of health as organic farmers when they use four or more PPE items. Hence, measures that encourage conventional cotton farmers to use more PPE during pesticide spraying or to adopt organic farming would substantially improve these farmers' health.

Keywords: pesticides, protective equipment, health, organic farming, smallholder farmers, cotton, Africa.

JEL codes: I12, I15, J28, O13, Q12, Q56.

[*]Department of Food and Resource Economics, University of Copenhagen, Denmark
[†]Laboratory of Analysis and Research on Economic and Social Dynamics, University of Parakou, Benin
[‡]Department of Food and Resource Economics, University of Copenhagen, Denmark
[§]Department of Economics, University of Copenhagen, Denmark

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Pesticides[1] are an integral part of the majority of today's agricultural production systems because they help to achieve and secure high yields, which are essential for providing sufficient food and plant-based materials for a growing global population. However, pesticides can damage the environment and jeopardize human health, particularly when handled inappropriately, as is often the case in developing countries. Farmers in developing countries are often unaware of the health hazards of inappropriate pesticide handling and frequently use excessive amounts of pesticides without adequate protective measures or training (e.g., Khan et al., 2015; Damalas and Abdollahzadeh, 2016; Hoi et al., 2016; Jallow et al., 2017; Sheahan and Barrett, 2017; Bagheri et al., 2018; Sharifzadeh et al., 2019). Furthermore, these farmers often use pesticides that have been banned in more developed countries because of their detrimental effects on the environment or human health (Wesseling et al., 1997; Ecobichon, 2001). The inappropriate handling of pesticides potentially leads to contamination of farmers, farm laborers, and their families with pesticides, which can result in acute or long-term health problems (Atreya et al., 2012; Gesesew et al., 2016; Chatzimichael et al., 2021). Unsurprisingly, various studies have found detrimental health effects of the use of pesticides by smallholder farmers in developing countries (e.g., Okello and Swinton, 2010; Athukorala et al., 2012; Atreya et al., 2012; Macharia et al., 2013a; Sheahan et al., 2017).[2] Given the private and social costs of these detrimental effects, it is highly relevant to analyze what could be done to reduce or avoid them.[3]

This paper investigates to what extent the use of personal protective equipment (PPE) can mitigate the adverse effects of pesticides on the health of smallholder cotton farmers in Benin, taking into account both the use of synthetic pesticides by conventional farmers and the use of bio-pesticides by organic farmers. Similarly to Sheahan et al. (2017), we use farm households' health expenditures as proxy for health outcomes,[4] but instead of comparing households that use pesticides with households that do not use pesticides, we focus on the effect of using PPE. While Okello and Swinton (2010) use a series of indicators for different measures of averting or mitigating exposure to pesticides, we measure PPE use by the number of different PPE items that are worn while handling and spraying pesticides, given that different PPE items likely have roughly additive effects as they protect different

[1]Throughout this article, we use the words "pests" and "pesticides" in their broad meanings, i.e., "pests" include, e.g., insects, fungi, weeds, arachnids, and other living organisms that negatively affect the performance of crops and "pesticides" include, e.g., insecticides, fungicides, herbicides, acaricides, plant growth regulators, and other substances that are applied to crops in order to protect them from negative effects of pests.

[2]Earlier studies include Antle and Capalbo (1994); Antle and Pingali (1994); Cole et al. (2000, 2002); and Maumbe and Swinton (2003).

[3]A detailed review of the literature about the relationship between pesticide handling and human health is given in Appendix Section A.

[4]Per-capita health expenditure is commonly used in empirical work as proxy for health outcomes, underpinned by Grossman's human capital theory (Grossman, 1972). Contamination with pesticides can not only lead to acute symptoms but, in the medium and longer term, also to illness, which even experts cannot determine for sure have been caused by contamination with pesticides. Total health expenditure includes the costs of treating all kinds of illnesses and, thus, has the advantage of covering illnesses that may potentially be long-term effects of pesticides but are difficult to prove as such.

parts of the body.[5] Several studies investigate drivers of PPE use (e.g., Karunamoorthi et al., 2011; Macharia et al., 2013b; Zapata Diomedi and Nauges, 2016), but these studies do not analyze the effects of these protective measures on the health of their users. Asfaw et al. (2010) and Okello and Swinton (2010) find that adopting developed-country standards for pesticide application is beneficial for the health of farmers in rural Kenya, but they do not specifically investigate PPE use. To the best of our knowledge, there is only one study—the conference paper of Macharia et al. (2013a)—that investigates the relationship between PPE use and pesticide-related health problems. Macharia et al. (2013a) show that PPE use is negatively associated with acute symptoms of pesticide poisoning. Our study is different, as we do not focus on acute symptoms but estimate the average treatment effect of PPE use on producers' general health outcomes, including both acute and longer-term effects.

We use a cross-sectional data set of 1,204 conventional and organic smallholder cotton farmers from three major cotton-growing districts in Benin. Benin is a highly relevant empirical case for our analysis for several reasons. First, cotton is by far the most important cash crop in many regions of Benin. Furthermore, both conventional cotton and organic cotton are produced side-by-side. Finally, conventional cotton farmers apply large amounts of pesticides[6] as they receive all the pesticides that they (potentially) need for their entire cotton farming on credit[7] from so-called "agricultural input import and distribution companies," while smallholder farmers in many other developing countries use only very limited amounts of pesticides due to liquidity constraints and limited availability on the market. Our regression analysis controls for variables that are likely related to both health expenditure and pesticide handling practices so that the analyzed *ceteris paribus* relationships are as close to causal relationships as possible. The results of this approach are confirmed by various robustness checks, including instrumental-variable estimations, genetic matching, and the approach suggested by Oster (2019) that takes into account the effect of potential omitted variables. Our empirical study shows that using PPE vastly reduces detrimental health effects of pesticides for conventional cotton farmers, while no effect was found for organic cotton farmers. If conventional cotton farmers simultaneously use at least four types of PPE, they have a similar state of health as organic cotton farmers. This indicates that synthetic pesticides have detrimental health effects on agricultural households if they are applied without adequate protective equipment, whereas the bio-pesticides used by organic cotton farmers in Benin do not significantly affect their health even when they are applied with little or no PPE. Our study demonstrates the effectiveness of measures for limiting health hazards of pesticides and, thus, can contribute to better targeted policies and more effective advice to farmers, extension agents, and other stakeholders. This in turn could result in more appropriate PPE use, lower health expenditures, and a better life for smallholder farmers in developing countries.

[5]Some PPE items protect the same part of the body but the farmers in our survey very rarely wear simultaneously PPE items that protect the same part of the body and the four mostly used PPE items, i.e., long trousers, boots, masks, and gloves (see Table 1), protect different parts of the body.

[6]For instance, in the 2019/20 cotton growing season in Benin, 665,703 ha were cultivated with conventional cotton and 4,845,612 liters of synthetic pesticides were applied to these cotton fields (**?**), which gives an average pesticide application rate of 7.3 l/ha.

[7]When the farmers sell their cotton after harvesting, the buyer of the cotton subtracts the costs of the received pesticides from the value of the sold cotton.

The rest of this article is organized as follows: Section 2 describes the data used for the analysis. Section 3 outlines our empirical strategy. The results are presented and discussed in Section 4. Finally, Section 5 contains our conclusions.

2 Data

2.1 Data collection

Our empirical analysis uses cross-sectional data collected between March and May 2018 by means of a household survey in three major cotton growing areas in Benin: the districts of Kandi, Pehunco, and Glazoué. These districts were selected due to the importance of cotton farming to the local economy, the co-existence of both conventional and organic cotton farming, and the consideration of regional diversity. In these districts, cotton farming is the primary source of income for most rural households, and the regional economies highly depend on cotton farming, trade, and processing. Maize, soybean, and sorghum are the main crops cultivated for food production and crop rotation with cotton. Pesticides are used extensively in conventional cotton farming (see Section 1), but are applied much less to other crops.

We obtained detailed village-level data for all 156 villages in the three districts that we selected for the survey, including the numbers of conventional and organic cotton farmers in each village, the total number of households, the importance of cotton farming as income source, the type of road to the village, sources of drinking water, etc. Since only 25 villages in the three districts were involved in organic cotton farming, all of them were selected for the survey. Then, we used genetic matching to select a second group of 25 villages for the survey: villages without organic cotton farming that had village-level characteristics which were very similar to the village-level characteristics of those with organic cotton farming. Finally, we used a search algorithm to select a third group of 25 villages: villages without organic cotton farming that were dissimilar to the villages in the first two groups and, thus, complemented these two groups such that the villages in all three groups together had, on average, village-level characteristics that were very similar to the average village-level characteristics of all villages in the respective district. This sampling procedure guaranteed (a) that we could select a sufficiently large number of organic cotton farmers for our survey, (b) that our survey covered villages without organic cotton farming that were similar to villages with organic cotton farming, enabling us to make comparisons between conventional and organic cotton farming, and (c) that the entire sample of villages could be seen as a representative sample of all cotton-producing villages in the three districts.[8]

Although we had initially planned to interview households in 75 villages, the interviews were ultimately conducted in 73. In Glazoué district, one village in the second group and one village in the third group had so few cotton farmers that the number of households that should have been

[8] The village-level characteristics that we used for selecting the second and third group of villages are presented in Appendix Section B.

interviewed according to our stratified random sampling strategy rounded to zero. In Kandi district, one village from the third group was inaccessible at the time of the survey so that the six farmers from this village who should have been interviewed could not be included in the survey. In Pehunco district, however, we gained an additional village when a hamlet of one village belonging to the first group at the time the villages were selected for the survey became an independent village by the time we conducted the interviews.

The households were selected through stratified random sampling, where the type of cotton farming and the village were used as strata. We aimed for a total sample of around 1,400 households and distributed the numbers of surveyed households among the three study areas proportionally to the total numbers of cotton farming households in these areas. We aimed to have 70% conventional cotton farming households and 30% organic cotton farming households in our sample in each of the three study areas, but this was only possible in Kandi and Glazoué, while there were too few organic cotton farming households in Pehunco. This procedure resulted in sampling intensities of 75%, 100%, and 55% for organic cotton farming households and sampling intensities of around 8%, 11%, and 8% for conventional cotton farming households in Kandi, Pehunco, and Glazoué, respectively.

Since we had a mobile phone number for each cotton-farming household in the selected villages, we managed to interview almost all selected households. In the few cases where the household was unavailable for the survey, we randomly selected another household from the same strata. In total, 1,361 households were interviewed. Eleven observations were removed due to missing values in crucial variables such as household composition, type of cotton farming, or health expenditure. In order to obtain more homogeneous groups of households with regard to exposure to pesticides or bio-pesticides, a further 17 households that produced both conventional and organic cotton were excluded, as well as 57 households that did not spray any pesticides or bio-pesticides themselves, and 72 households producing organic cotton without certification (e.g., because they switched to organic farming less than three years before or had recently violated rules for organic farming, for instance by using synthetic pesticides). Hence, the sample used in the empirical analysis consisted of 1,204 households, of which 1,001 produced conventional cotton and 203 produced organic cotton.

The survey gathered information on various types of household characteristics and very detailed information on cotton farming in the growing season from June 2017 to March 2018, including the PPE used when applying pesticides and annual health expenditure subdivided into: expenditures at health facilities, expenditures on medicines, and expenditures on traditional health treatments. For some of the households interviewed, the cotton fields were divided among two or more household members who managed their cotton fields independently of each other.[9] Our analysis always considers the cotton farming (e.g., area cultivated with cotton, costs of different types of pesticides, labor used for pesticide applications, etc.) of the entire household. For producer-specific variables (e.g., training in pesticide application, PPE use, etc.), our analysis uses the responses of the household head if he or she is responsible for at least a part of the household's cotton farming. Otherwise we use the

[9] Appendix Section C provides URLs for downloading the questionnaires that were used for the survey.

responses of the household member who is responsible for the largest cotton-growing area among the household members.

2.2 Descriptive statistics

In our sample (see Section 2.1), all households sprayed pesticides or bio-pesticides, where the vast majority of the spraying was done by household members and only a minimal part of the spraying was done by hired laborers (Table 1). With the larger cotton-growing areas per household and more frequent pesticide applications in conventional cotton farming compared to organic, conventional farmers used much more time on spraying pesticides and, thus, are potentially more exposed to pesticides than organic farmers. Almost two-thirds of the conventional households[10] used glyphosate, a well-known but controversial herbicide that is suspected of producing negative health effects. Bio-pesticides are also considered as there is no clear evidence of their effect on health. One could expect that households might try to reduce the risk of detrimental health effects from pesticides by wearing PPE when they apply glyphosate, other synthetic pesticides, or bio-pesticides. To measure farmers' PPE use, both conventional and organic households were asked which types of PPE they wore when they sprayed pesticides on their plots. Seven different types of PPE were used by the interviewed households, with the most frequently used PPE being long trousers (86%), followed by boots (36%), masks (35%), and gloves (30%). A small fraction of the interviewed households used overalls (13%), coats (13%), or goggles (13%). In general, conventional households wore more PPE, and also wore more frequently at least one PPE item, than organic households (Table 1). These significant differences could be explained by the common view that synthetic pesticides are more harmful than bio-pesticides. Compared to conventional households, a larger proportion of organic households participated in training in pesticide application, and a lower proportion of them ate while spraying pesticides.

Table 1 also presents socio-economic characteristics of the households. Overall, the level of education of the household heads is very low, with an average of 1.37 years and with no statistically significant difference between conventional and organic households. We also do not observe significant differences in age of the household head, experience in cotton farming, household size, composition of the household, or water deprivation (i.e., using an unsafe source of drinking water as classified by the WHO or needing more than 30 minutes to collect drinking water). In contrast, we find a significantly larger share of male household heads, a larger area cultivated with cotton, more wealth (ownership of assets), and higher health expenditure among conventional households compared to organic households (Table 1). We find a very large difference in the variable "health attitude" that we obtained by asking the farmers "Which type of cotton farming do you think is better for the health of the workers on your cotton plots (including you and your family)?" on a 7-point Likert scale, where a one indicates that organic cotton is much better, a seven indicates that conventional cotton is much

[10]As the terms "households that practice conventional farming" and "households that practice organic farming" make sentences unnecessarily long and frequently unclear, we abbreviate these two types of farm households to "conventional households" and "organic households," respectively.

better and a four indicates that both types of cotton farming have about the same effect on the health. While 98% of the organic farmers state that organic cotton is better for the health, there is a considerable heterogeneity among conventional farmers, with 60% stating that organic cotton is better and 29% stating that conventional cotton is better for health.

3 Empirical Strategy

3.1 Model specification

The type of pesticide, the duration and frequency of its handling, and the use of averting measures such as safe handling practices or PPE determine the exposure of farmers and their families to pesticides (Antle et al., 1998; Okello and Swinton, 2010). Greater exposure may increase the risk of health problems and, in consequence, the household's health expenditure, because patients usually have to pay for medical treatments in Benin. In our empirical analysis, we investigate how PPE use and other covariates affect the health of farmers and their families, proxied by per-capita health expenditure, using the following regression model:

$$\tilde{y}_i = \beta_0 + \delta\, D_i + \theta\, P_i + \lambda\, P_i\, D_i + \beta'\, x_i + \gamma'\, x_i^d\, D_i + \varepsilon_i, \tag{1}$$

where $\tilde{y}_i$ is a measure of per-capita health expenditure of household i, which includes expenditures at hospitals, expenditures for medicines, and expenditures for traditional medical treatment. D_i is a dummy variable that indicates the type of cotton farming, with $D_i = 0$ indicating conventional and $D_i = 1$ indicating organic cotton, and P_i being the number of PPE items used when applying pesticides. The vector x_i consists of covariates that likely affect the household's health expenditure, namely gender, age of household head, years of education, experience in cotton farming, household size, dependency ratio, household assets (logarithm, in million FCFA), water deprivation, land cultivated with cotton (logarithm, in ha), training on pesticide application, bathing after pesticide application, eating during pesticide application, and health attitude. The vector x_i^d is a subset of the covariates in x_i that likely have different effects on conventional and organic households, namely training on pesticide application, bathing after pesticide application, and eating during pesticide application. While ε_i is an error term, β_0, δ, θ, and λ are coefficients and β and γ are vectors of coefficients to be estimated. We include the interaction terms $P_i\, D_i$ and $x_i^d\, D_i$ in order to take into account that conventional and organic farming methods use different types of pesticides and apply pesticides in different frequencies (see, e.g., Section 2.2) so that the PPE use and some other covariates (e.g., the potential exposure to pesticides) likely have different health effects on conventional and organic households.

As the dependent variable of our analysis, the per-capita health expenditure, is highly right-skewed and contains observations with true zeros, we transform it by the inverse hyperbolic sine (IHS) function, i.e., $\tilde{y}_i = \operatorname{arc\,sinh}(y_i) = \log\left(y_i + \sqrt{y_i^2 + 1}\right)$. The IHS transformation is similar to the logarithmic transformation, but it can be applied to zero values (see, e.g., Johnson, 1949; Burbidge et al., 1988).

Table 1: Descriptive statistics of conventional and organic cotton farming households

	Missing	All	Convent.	Organic	Diff.	P-value
Household head						
Age	0	42.07	41.90	42.92	-1.02	0.284
Sex (1=male)	0	0.94	0.96	0.88	0.07	<0.001
Years of education	0	1.37	1.32	1.58	-0.25	0.303
Experience in cotton farming (years)	0	15.07	15.16	14.59	0.57	0.416
Health attitude	0	3.00	3.33	1.35	1.97	<0.001
Household						
Household size	0	7.35	7.41	7.08	0.33	0.241
Number aged 0-14	0	3.19	3.22	3.04	0.18	0.306
Number aged 15-35	0	3.00	3.03	2.85	0.18	0.226
Number aged 36-65	0	1.10	1.09	1.12	-0.03	0.729
Number aged $\geq$ 66	0	0.07	0.06	0.07	-0.00	0.855
Dependency ratio	0	0.41	0.41	0.42	-0.00	0.927
Land cultivated with cotton (ha)	0	3.46	3.86	1.50	2.36	<0.001
Total land owned (ha)	0	13.14	13.59	10.88	2.71	0.168
Household assets (million FCFA)	0	2.31	2.45	1.66	0.79	0.001
Water deprivation	0	0.35	0.34	0.39	-0.05	0.197
Health expenditure (1,000 FCFA/year)	0	87.28	94.51	51.62	42.89	<0.001
Health exp. per person (1,000 FCFA/year)	0	13.14	14.32	7.32	7.00	<0.001
No health expenditure	0	0.09	0.09	0.09	0.01	0.919
Pesticide application						
by household labor (hours/year)	0	142.74	159.72	59.00	100.72	<0.001
by hired labor (hours/year)	0	4.12	4.78	0.86	3.92	0.007
Costs of herbicides (1,000 FCFA/year)	1	44.50	53.53	0.00	53.53	<0.001
Costs of insecticides (1,000 FCFA/year)	0	99.87	120.12	0.00	120.12	<0.001
Costs of biopesticides (1,000 FCFA/year)	3	4.10	0.00	24.48	-24.48	<0.001
Training in pesticide application	0	0.16	0.12	0.34	-0.23	<0.001
Bathing after pesticide application	0	0.69	0.70	0.63	0.07	0.079
Eating during pesticide application	0	0.14	0.15	0.09	0.06	0.040
Use of any PPE	0	0.96	0.97	0.89	0.09	<0.001
Number of PPE used	0	2.25	2.37	1.67	0.70	<0.001
Use of long trousers	0	0.86	0.88	0.79	0.09	0.001
Use of overalls	0	0.13	0.14	0.06	0.08	0.003
Use of coat	0	0.13	0.15	0.03	0.12	<0.001
Use of boots	0	0.36	0.39	0.18	0.21	<0.001
Use of gloves	0	0.30	0.31	0.23	0.08	0.021
Use of goggles	0	0.13	0.14	0.07	0.07	0.006
Use of mask	0	0.35	0.35	0.32	0.04	0.347
District						<0.001
Kandi	0	0.58	0.54	0.79	-0.25	
Pehunco	0	0.24	0.28	0.03	0.25	
Glazoué	0	0.18	0.18	0.18	-0.00	
Observations		1204	1001	203		

Notes: PPE = personal protective equipment; column 'Missing' indicates the number of missing values; the following three columns indicate mean values or proportions of the variables for all households, conventional households, and organic households, respectively; column 'Diff.' indicates the difference in the mean values or proportions between conventional and organic households; column 'P-value' indicates P-values obtained from two-sample t-tests for equality of mean values for continuous variables and P-values of Pearson's χ^2-tests for equal proportions for binary and categorical variables. At the time of the survey, 1,000 FCFA corresponded to around 1.52 EUR or 1.88 USD.

As regression results are not invariant to the units of measurement for IHS-transformed variables, we choose the unit of measurement for the per-capita health expenditure by the method suggested by Aïhounton and Henningsen (2021). On the basis of several diagnostic criteria, measuring per-capita health expenditure in 1,000 FCFA seems to be the most suitable in our empirical model specification (see Table H.1 in Appendix Section H).

We estimate equation (1) both by OLS and left-censored Tobit regression, where the latter takes into account that the dependent variable is left-censored at zero with 9% of the observations being censored (see Table 1). In order to account for location-specific effects, we use arrondissement-fixed effects and calculate standard errors that are robust to clustering at the arrondissement level using clustered sandwich estimators of type "HC1" in the terminology of MacKinnon and White (1985) (for details see, e.g., Berger et al., 2017).[11]

When we assess the effects of PPE use and other covariates on the per-capita health expenditure, we take into account the interaction terms (if present) and calculate the respective semi-elasticities or elasticities based on the derivations by Bellemare and Wichman (2020). For instance, we calculate the semi-elasticity that indicates the relative change of the per-capita health expenditure when the number of PPE increases by one item with: $\tilde{\varepsilon}_{(y_i/P_i)} = \left(\hat{\theta} + \hat{\lambda} D_i\right) \sqrt{y_i^2 + 1} \Big/ y_i$. Furthermore, we calculate the semi-elasticity that indicates the relative change of per-capita health expenditure when a household switches from conventional to organic cotton farming by:

$$\tilde{\varepsilon}_{(y_i/D_i)} = \frac{\sinh\left(\beta_0 + \hat{\delta} + \hat{\theta}\, P_i + \hat{\lambda}\, P_i + \hat{\beta}\, x_i + \hat{\gamma} x_i^d + \varepsilon_i\right)}{\sinh\left(\beta_0 + \hat{\theta}\, P_i + \hat{\beta}\, x_i + \varepsilon_i\right)} - 1 \quad (2)$$

$$= \frac{\sinh\left(\tilde{y}_i + \left(\hat{\delta} + \hat{\lambda} P_i + \hat{\gamma} x_i^d\right)(1 - D_i)\right)}{\sinh\left(\tilde{y}_i - \left(\hat{\delta} + \hat{\lambda} P_i + \hat{\gamma} x_i^d\right) D_i\right)} - 1. \quad (3)$$

In addition, we investigate the effect of switching from conventional to organic cotton farming on per-capita health expenditure by genetic matching that minimizes the differences in observed characteristics between the matched control and treatment groups (Diamond and Sekhon, 2013).[12] We do this by considering two cases. First, conventional and organic farmers are matched based on propensity scores, all covariates x_i that are statistically significant at 10% level in at least one of our three main regression models (columns 2–4 of Table 3), and the number of PPE items used (P_i). Based on the matching of these variables, we obtain the average treatment effect of switching from conventional to organic farming when keeping the number of PPE items constant. Second, conventional and

[11] The households in our data set are located in three different districts, 14 different arrondissements, and 73 different villages. In basically all our model specifications, Wald tests and likelihood-ratio tests reject district-fixed effects in favor of arrondissement-fixed effects. We do not use village-fixed effects, because there are several small villages in our data set with only very few observations (e.g., there are seven villages with only two observations and four villages with only three observations). As villages in the same arrondissement usually have very similar characteristics, e.g., regarding the availability and prices of medical treatments and PPE items, we expect that arrondissement-fixed effects and accounting for clustering at the arondissement level sufficiently control for differences in spatial heterogeneity.

[12] A detailed description of the matching approach that we used is available in Appendix Section G.

organic farmers are matched based on propensity scores and the same subset of covariates x_i as before but not on the number of PPE items used (P_i). In this case, we obtain the average treatment effect while taking into account that switching to organic cotton may result in using a different number of PPE items.

3.2 Identification strategy

Our econometric approach to estimate the effect of PPE use on per-capita health expenditure relies on a selection-on-observables identification strategy. In order to assess the consistency of our estimators, we discuss three potential sources of statistical endogeneity: measurement errors, reverse causality, and unobserved heterogeneity. Measurement errors are unavoidable in data obtained in a recall-based survey, but we tried to minimize them in the data collection. We do not expect measurement errors in our variable that indicates whether a household produces conventional or organic cotton because we confirmed the information obtained from households with leaders of farmers' organizations and extension officers. Furthermore, organic households are closely monitored by global buyers for violations of the rules for organic farming. In order to avoid that respondents forget to report certain types of health expenditure and certain types of PPE, we asked separate questions for three different types of health expenditure (i.e., expenditures at hospitals, expenditures for medicines, and expenditures for traditional medical treatment) and seven different types of PPE. Random measurement errors in the health expenditure are absorbed by the error term. Even systematic underreporting of health expenditure (e.g., if some respondents do not remember some of their households' health expenditures) does not affect our estimates of the relative effect on health expenditure if these measurement errors are on average roughly proportional to the 'true' health expenditure and are not correlated to the observed PPE use or the adoption of organic farming, which we consider to be reasonable assumptions for our data set. Random measurement errors in the number of PPE items, which are expected to be very small, bias our estimates towards zero. Hence, we can rule out that measurement errors result in an overestimation of the effects of PPE and of switching to organic farming on health expenditure.

Our estimator of the effect of PPE on per-capita health expenditure would be affected by reverse causality if health expenditure has a causal effect on the number of PPE items used. Health problems and, thus, higher health expenditure could perhaps motivate farmers to care more for their health and encourage them to use more PPE items. However, health expenditure observed in our survey covers the 12 months before the survey (i.e., from around April 2017 to around April 2018), while the main spraying and, thus, the PPE use covered in our survey took place from June to September 2017. Hence, only health expenditure in the first few months of the observation period could affect PPE use, while health expenditure during most of the observation period could not have influenced PPE use. Hence, we consider potential reverse causality problems to be negligible in our analysis.

In order to prevent our estimates of the effects of PPE on health expenditure from being affected by unobserved heterogeneity, the covariates in our regression equation (1) must include all variables that simultaneously affect health expenditure and the number of PPE items. The first column of the

Table 2: Identification strategy

Factors that potentially affect both PPE use and per-capita health expenditure	
Omitted variables	Proxy variables
Exposure to pesticides and their toxicity	Type of cotton farming, cotton land size (total value of pesticides)
Wealth	Value of household assets, total land ownership
Risk attitudes	Age and gender of household head, dependency ratio
Knowledge about health	Education
Attitudes towards toxic substances	Evaluation of health effects of conventional vs. organic cotton farming ("health attitude"), type of cotton farming
Other controls	Training in pesticide management, eating while spraying, bathing after spraying, water deprivation, arrondissement-fixed effects
Factors that potentially affect both switching to organic farming and per-capita health expenditure	
Omitted variables	Proxy variables
Household size and composition	Household size, dependency ratio
Wealth	Total land ownership, value of household assets
Risk attitudes	Age and gender of household head, dependency ratio
Knowledge about health	Education
Attitudes towards toxic substances	Evaluation of health effects of conventional vs. organic cotton farming ("health attitude")
Other controls	Water deprivation, arrondissement-fixed effects

upper part of Table 2 lists all the factors that we consider to potentially affect both health expenditure and the number of PPE items. As these factors are rather general and difficult to observe, the second column of the upper part of Table 2 lists observable variables that we use as proxies for the variables in the first column.

Given that exposure to toxic pesticides can negatively affect health, the quantity and toxicity of pesticides to which farmers are exposed likely affect their health expenditure. Furthermore, the more pesticides farmers apply and the greater their toxicity, the larger the benefit from wearing PPE and, thus, the more PPE items the farmers can be expected to wear. The type of cotton farming and the size of the land planted to cotton are used as proxies for the quantity and toxicity of pesticides to which farmers are exposed. The quantity of applied pesticides largely depends on the cotton land size and the type of cotton farming because pesticide application rates are similar for the same type of cotton farming, other crops than cotton are rarely treated with pesticides, and organic farmers apply significantly less pesticide than conventional farmers. The toxicity of the applied pesticides largely depends on the type of cotton farming given that the types of applied pesticides are rather homogeneous for each type of cotton farming and that synthetic pesticides applied by conventional farmers are considered to be more toxic than bio-pesticides applied by organic farmers. Given that the price of each pesticide is usually the same for all farmers in our data set, the total value of all applied pesticides can be seen as a price-weighted quantity index of the applied pesticides and, thus, can be used as an alternative proxy for the quantity of pesticides.

As households in Benin have to pay for medical treatments, it is likely that the wealth of a household has a positive effect on its health expenditures because wealthier households are more likely to seek treatment and likely choose a more expensive treatment in case of health problems. Similarly, wealthier households would, *ceteris paribus,* use more PPE items than poorer households given that they have more resources for purchasing PPE. The monetary value of household assets and the total land ownership are used as proxies for wealth because the more assets and land a household owns, the more resources this household likely has at its disposal for purchasing PPE items and paying for medical treatments.

Moreover, the risk aversion of a household likely affects its health expenditures, such as those due to injuries caused by risky behavior, health problems caused by smoking or alcohol, or health expenditures for preventive measures. More risk-averse households are probably less willing to accept a higher risk of contamination with pesticides and, thus, more likely to wear PPE. The age and sex of the household head and the dependency ratio are used as proxies for the household's risk attitudes because households with more children and with female and older household heads are expected to be more risk averse (see, e.g., Dosman et al., 2001) and, thus, less likely to take health risks and more likely to wear PPE.

Knowledge about health is expected to affect health expenditure, e.g., through a healthier lifestyle or more preventive (medical) measures, including more knowledge about adverse health effects of pesticides and a higher PPE use. The education of the household head is used as a proxy for knowledge about health, assuming that basic education and literacy are required to understand and learn about health.

A household's perceptions of the health effects of potentially toxic substances can also affect its health expenditure, e.g., through its effort to avoid contamination with toxic pesticides, including the use of PPE. The households' stated evaluations of the health effects of conventional vs. organic cotton farming (variable "health attitude" as explained in Section 2.2)[13] and the type of cotton farming are used as proxies for their perception of health effects of potentially toxic substances. A household's evaluation of the health effects of conventional vs. organic cotton farming likely indicates its attitudes towards avoiding negative health effects of synthetic pesticides and other potentially toxic substances. Moreover, organic farmers are expected to be, on average, more cautious about potentially toxic substances than conventional farmers because their attitudes towards the health effects of pesticides

[13]The use of this variable in our selection-on-observables identification strategy is inspired by Verhofstadt and Maertens (2014) who use a selection-on-observables identification strategy with willingness-to-pay (WTP) to join cooperatives as one of the explanatory variables to estimate the causal effects of smallholder cooperatives on agricultural performance, as well as by Bellemare and Novak (2017) who use a similar approach with a measure of willingness-to-pay (WTP) to join contract farming as one of the explanatory variables to estimate the causal effect of contract farming on food security.

and other potentially toxic substances may have affected their decision to be a conventional or an organic farmer.

We also control for whether households received any pesticide management training, whether household members eat while spraying (which increases the probability of pesticide contamination), and whether they bathe right after spraying (which likely reduces pesticide contamination). These variables are expected to affect health expenditure and could also directly affect PPE use or could be related to unobserved variables that affect PPE use. Water deprivation is also included as an additional control variable because water-deprived households may be more prone to illnesses due to using unsafe water sources and, thus, may have higher health expenditure. Additionally, arrondissement-fixed effects are used to capture differences between arrondissements in terms of availability and prices of both medical treatments and PPE items, which can result in both differences in health expenditure and in PPE use.

While the primary aim of our analysis is to estimate the effect of PPE use on per-capita health expenditure, our secondary aim is to estimate the effect of switching to organic farming on health expenditure. We use a selection-on-observables identification strategy also for this aim of our analysis: i.e., the covariates in our regression equation (1) must include all variables that simultaneously affect health expenditure and the decision to switch to organic farming. The lower part of Table 2 lists factors that could simultaneously affect health expenditure and the decision to switch to organic farming and the proxy variables that we include in our regression analysis to control for these factors.

Finally, three additional approaches are used to check the robustness of our econometric specification: genetic matching[14], the approach to assess sensitivity to omitted variables suggested by Oster (2019)[15], and instrumental-variable regression.

4 Results[16]

4.1 Graphical analysis

Before presenting the regression results, we visually analyze the relationship between the three main variables of interest of our empirical analysis: the cotton farming method (conventional or organic), PPE use, and per-capita health expenditure. Figure 1 illustrates the distribution of the per-capita health expenditure for conventional and organic households by a kernel density plot. The figure indicates that organic households tend to have lower per-capita health expenditure than conventional households, which may indicate that members of organic households are on average healthier than members of conventional households.

[14] A detailed description is given in Appendix Section G. Matching approaches basically rely on the same assumptions about omitted variables as OLS regressions but matching approaches have the advantage that they do not assume linearity between the covariates and the outcome variable.

[15] A detailed description is given in Appendix Section D.

[16] The empirical analyses were performed and all results were obtained with the statistical software "R" (R Core Team, 2021). The add-on packages that we used are listed in Appendix Section J.

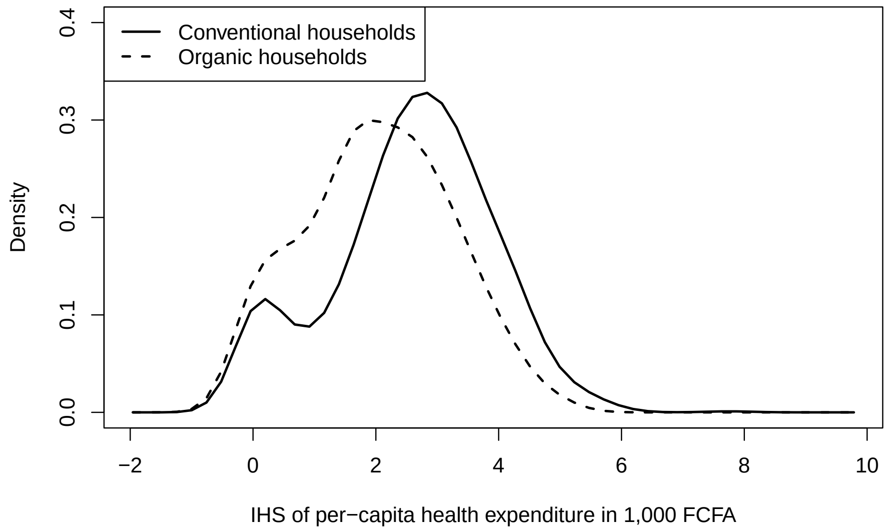

Figure 1: Kernel density estimation of per-capita health expenditure of conventional and organic households (using the IHS transformation as explained in Section 3.1)

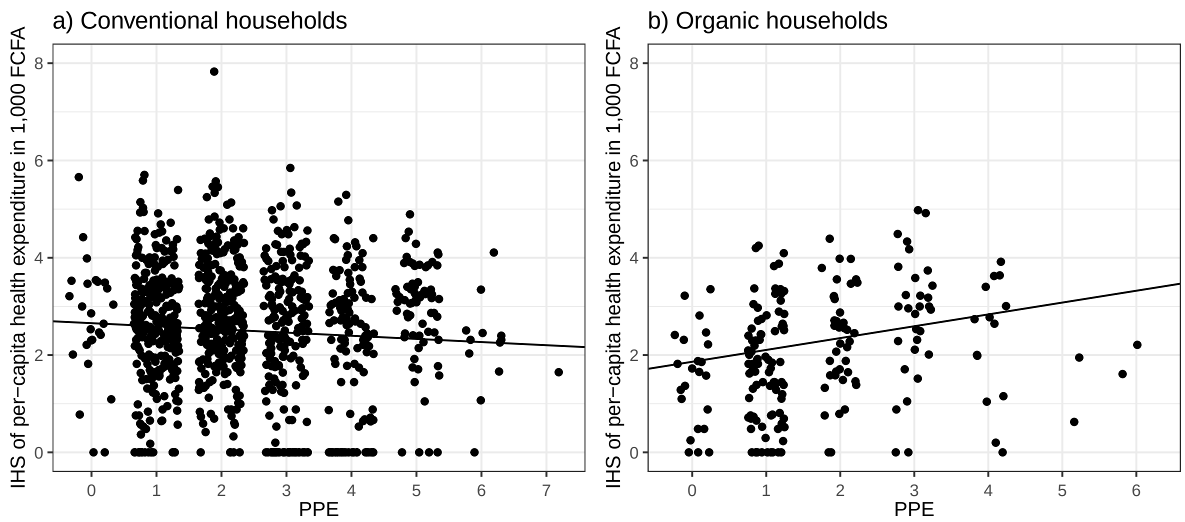

Figure 2: Relationship between per-capita health expenditure and number of PPE items for conventional and organic households (using the IHS transformation of per-capita health expenditure as explained in Section 3.1)

Figure 2 uses jitter plots to illustrate the relationship between per-capita health expenditure and the number of PPE items for conventional and organic households. The left panel of this figure indicates a very slight negative relationship between PPE items and per-capita health expenditure for conventional households. In contrast, the right panel of this figure indicates a notable positive relationship between PPE items and per-capita health expenditure for organic households. However, very few organic households use more than three PPE items and, thus, this relationship may not hold true for more than three PPE items.

4.2 Regression results

We investigate the effect of the number of PPE items used while spraying pesticides on per-capita health expenditure based on the regression model specified in equation (1). Table 3 presents the results from three OLS estimations and one Tobit regression with left-censoring at zero. The first specification is a "short regression" with only the number of PPE items, the type of cotton farming, and the interaction term between these variables as explanatory variables (see equation (D.1) in Appendix Section D). In the second specification, we control for a number of covariates except for "health attitude" and in the third specification, we control for all covariates described in Table 2, i.e., including "health attitude". The left-censored Tobit regression is used to account for the presence of households with 'true' zero values in the health expenditure (9% of the households, see Table 1).[17]

The most relevant results for answering our research questions are the semi-elasticities of PPE and the semi-elasticity of switching to organic farming (see Section 3.1). The "short regression" (column 1) confirms the results of our graphical analysis: for conventional households, health expenditure is not significantly associated with the number of PPE items used, while for organic households, there is a considerable and highly statistically significant positive association between health expenditure and the number of PPE items used. However, if we add covariates to control for differences between households that use no or few PPE items and households that use many PPE items, we find in all specifications (columns $2-4$) that PPE use significantly reduces per-capita health expenditure of conventional households, while no significant effect can be found for organic households. The effect of using PPE on the per-capita health expenditure of conventional households is not only statistically significant but is also substantial in size: using one additional PPE item reduces the health expenditure by 14 to 17%.

Since many relevant control variables such as wealth (proxied by the value of household assets)[18] and exposure to pesticides (proxied by the land area cultivated with cotton)[19] are expected to positively affect both PPE use and per-capita health expenditure, controlling for these covariates vastly reduces the estimated semi-elasticities of PPE. For conventional households, adding control variables makes the small and statistically insignificant semi-elasticity of the PPE in the "short regression" to become substantially negative and statistically significant. In contrast, for organic households, adding control variables moves the substantially positive and statistically significant semi-elasticity of PPE in the "short regression" towards zero and makes it statistically insignificant (compare columns 1 and 2).

[17] The lower log-likelihood value of the Tobit regression (column 4) compared to the log-likelihood value of the corresponding OLS regression (column 3) indicates that taking into account the censoring of the dependent variable does not considerably improve the fit of the regression model.

[18] As explained in Section 3.2, we control for the household's capacity to accommodate medical expenses and purchase PPE through a proxy variable measuring the total monetary value of household assets. We found that a 1% increase in household wealth is associated with a $0.25-0.27$% increase in per-capita health expenditure. This estimate is in line with Sheahan et al. (2017) who report a positive association between household income and household health expenditures.

[19] The OLS regression without "health attitude" and the Tobit regression of the full model (columns 2 and 4 of Table 3) indicate that the land area cultivated with cotton is positively associated with per-capita health expenditure for conventional households. As elaborated in Section 3.2, conventional households receive synthetic pesticides proportional to the land area cultivated with cotton. Hence, these results indicate that an increased use of synthetic pesticides is associated with more detrimental health effects.

Table 3: OLS and Tobit regression results

	IHS of per-capita health expenditure			
	OLS (short)	OLS (no health att.)	OLS (full)	Tobit
	(1)	(2)	(3)	(4)
PPE	−0.06 (0.07)	−0.17** (0.07)	−0.14** (0.06)	−0.17** (0.08)
Organic	−1.10*** (0.18)	−0.80*** (0.23)	−0.96*** (0.28)	−0.99*** (0.29)
Gender (male)		−0.02 (0.17)	−0.01 (0.17)	−0.02 (0.18)
Age of household head		0.004 (0.004)	0.003 (0.003)	0.004 (0.003)
Years of education		0.01 (0.01)	0.02 (0.01)	0.02 (0.02)
Experience in cotton production		−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
Household size		−0.03 (0.02)	−0.03* (0.02)	−0.03* (0.02)
Dependency ratio		0.27 (0.29)	0.28 (0.24)	0.33 (0.27)
log(Household assets)		0.25*** (0.05)	0.26*** (0.05)	0.27*** (0.05)
Water deprivation		0.08 (0.08)	0.06 (0.09)	0.07 (0.10)
log(Land cultivated with cotton)		0.15* (0.09)	0.13 (0.08)	0.15* (0.09)
Training in pesticide application		0.42** (0.17)	0.35** (0.14)	0.37*** (0.14)
Bathing after pesticide application		0.12 (0.15)	0.17 (0.14)	0.21 (0.16)
Eating during pesticide application		0.18 (0.27)	0.43* (0.25)	0.45* (0.24)
Health attitude			−0.13*** (0.03)	−0.15*** (0.03)
PPE * Organic	0.31*** (0.07)	0.24*** (0.07)	0.23*** (0.07)	0.25*** (0.07)
Organic * log(Land cultivated with cotton)		−0.09** (0.05)	−0.11** (0.05)	−0.14** (0.06)
Organic * Training in pesticide application		−0.31* (0.16)	−0.27 (0.20)	−0.31 (0.21)
Organic * Bathing after pesticide application		0.49 (0.37)	0.40 (0.38)	0.43 (0.42)
Organic * Eating during pesticide application		−0.20 (0.32)	−0.40 (0.28)	−0.44 (0.27)
Constant	2.72*** (0.16)	−0.86 (0.64)	−0.61 (0.56)	
Arrondissement-fixed effects	Yes	Yes	Yes	Yes
Semi-elasticity: PPE (Conventional)	−0.06 (0.07)	−0.17 (0.07)**	−0.14 (0.06)**	−0.17 (0.08)**
Semi-elasticity: PPE (Organic)	0.25 (0.08)***	0.08 (0.10)	0.09 (0.09)	0.09 (0.09)
Semi-elasticity: Organic	−0.34 (0.09)***	−0.11 (0.12)	−0.34 (0.12)***	−0.34 (0.12)***
Log-likelihood	−2001.19	−1874.21	−1849.43	−1902.66
Akaike's Inf. Crit.	4012.38	3816.41	3768.85	3875.33
Bayesian Inf. Crit.	4037.85	3989.59	3947.12	4053.60
Observations	1204	1204	1204	1204
R squared	0.04	0.22	0.25	

Notes: Significance codes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The values in parentheses are cluster-robust standard errors. The estimates of the Tobit regression in column (4) are the marginal effects. 'Semi-elasticity: PPE (Conventional)' indicates the semi-elasticity of PPE calculated for an average conventional household. 'Semi-elasticity: PPE (Organic)' indicates the semi-elasticity of PPE calculated for an average organic household. 'Semi-elasticity: Organic' indicates the relative effect of switching from conventional to organic farming calculated at the sample mean as defined in equation (3). The standard errors of the semi-elasticities are calculated with the delta method as described in Appendix Section F.

The control variable “health attitude” is expected to positively affect PPE use but to negatively affect health expenditure (e.g., through a healthier way of life). Hence, including health attitude as a covariate has the opposite effect on the semi-elasticities of PPE as including covariates such as wealth and exposure to pesticides. However, the effect of including health attitude as covariate is relatively small (compare columns 2 and 3).[20] Controlling for health attitude reduces the magnitude of the estimated semi-elasticity of PPE for conventional households by three percentage points (corresponding to 17%), which means that we would overestimate the effect of PPE on per-capita health expenditure when we exclude health attitude as explanatory variable. Since this variable is a proxy for unobserved heterogeneity, such as farmers’ preferences, abilities, and personal traits, the inclusion of this variable in the model specification gives more reliable estimates.

Figure 3 visualizes the effect of PPE on per-capita health expenditure for conventional and organic households, holding the continuous and integer variables constant at their sample mean values, the binary variables constant at their proportions in the sample, and the arrondissement constant at its modal value. When using few PPE items, conventional households have, *ceteris paribus,* significantly higher per-capita health expenditure than organic households. However, increasing PPE use decreases the difference in per-capita health expenditure and makes it statistically insignificant. Our results indicate that a conventional household no longer has a higher health expenditure than a corresponding organic household if it uses four or more PPE items while spraying pesticides. However, it must be noted that very few organic households use more than three PPE items (see, e.g., Figure 2), which limits the reliability of comparing conventional and organic households with four or more PPE items. As most households use only one or two PPE items, our results indicate that most households could substantially reduce their per-capita health expenditure by switching from conventional to organic farming. Controlling for health attitude, which is heavily associated with the decision to adopt organic farming, our results indicate that switching from conventional to organic farming reduces the per-capita health expenditure of a typical household by 34%. Our analysis based on genetic matching with and without PPE as a covariate indicates that switching to organic cotton reduces per-capita health expenditure by 41% and 43%, respectively, which is slightly larger than indicated by our OLS estimates (Table 4).

Overall, our results indicate that the use of synthetic pesticides in conventional farming has substantial detrimental effects on the health of farmers and their household members, as indicated by vastly increased per-capita health expenditures. However, PPE use while spraying can vastly reduce these detrimental health effects. Already wearing four PPE items while spraying, e.g., long trousers, boots, masks, and gloves (which are the four most frequently used PPE items) strongly protects against detrimental health effects of synthetic pesticides and by this reduces the health expenditure of conventional households to a level similar to that of organic households.

[20] When we control for “health attitude”, eating while spraying becomes significantly positively associated with per-capita health expenditure. Eating while spraying vastly increases the risk of contamination with pesticides and, thus, it is not surprising that it is positively associated with per-capita health expenditure.

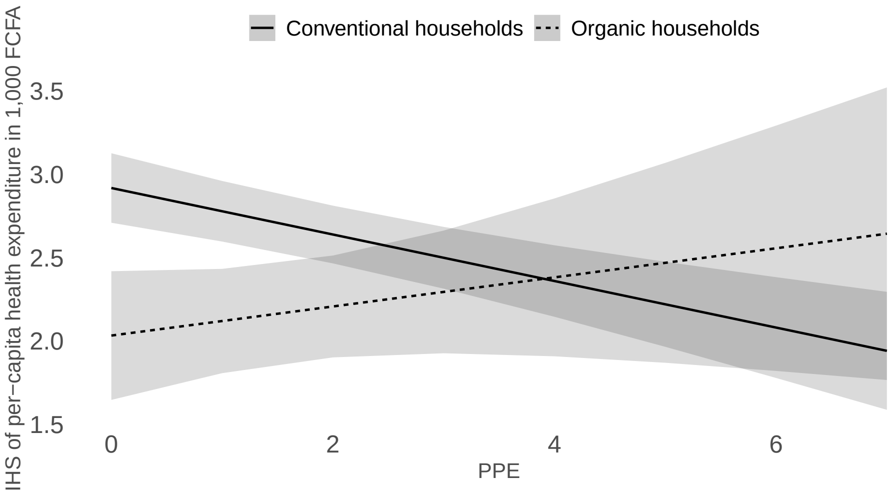

Figure 3: Predicted per-capita health expenditure for conventional and organic households (using the IHS transformation of per-capita health expenditure as explained in Section 3.1)

Table 4: Results of the genetic matching

	Matching with PPE	Matching without PPE
Semi-elasticity of switching to organic farming	-0.41 (0.04)***	-0.43 (0.04)***
Original total number of households	1204	1204
Original number of organic households	203	203
Original number of conventional households	1001	1001
Number of matched pairs of households	310	396
Number of matched unique organic households	88	103
Number of matched unique conventional households	222	293

Notes: Significance codes: *p<0.1; **p<0.05; ***p<0.01. The values in parentheses are standard errors.

Assuming that unobserved variables that are not proxied by any of our covariates affect PPE use and the per-capita health expenditure of *conventional* households in a similar way as they do for *organic* households, our results for *organic* households indicate that the estimated negative effect of PPE use on the per-capita health expenditure of *conventional* households is not a result of an omitted-variable bias. If omitted variables would downward-bias the estimated effect of PPE use on per-capita health expenditure, we would find a negative estimate of the effect both for conventional and for organic households. As we find a slightly positive (and statistically insignificant) effect for organic households and we can exclude that PPE use has in reality a positive effect on the per-capita health expenditure of organic households, we conclude that the estimated negative effect of PPE use on the per-capita health expenditure of conventional households cannot be caused by an omitted-variable bias. In contrast, if omitted variables would bias the estimated effect of PPE use on per-capita health expenditure upwards to a substantial degree, our results would indicate that PPE use reduces the per-capita health expenditure of organic households as well, while the negative effect of PPE use on the per-capita health expenditure of conventional households is even larger (in absolute terms) than our estimates indicate. Hence, we can conclude that our estimates do not overestimate how much PPE use reduces the per-capita health expenditure of the farm households in our study area.

4.3 Sensitivity to omitted variables

In order to assess the sensitivity of our analysis to omitted variables, we apply the approach suggested by Oster (2019). Table 5 presents the bias-adjusted coefficients of the three main explanatory variables of our analysis that we calculated for four different values of the assumed R^2-value of a hypothetical regression model with all relevant (observed and unobserved) explanatory variables (R_h): $R_h = 1.25\,R$, $R_h = 1.50\,R$, $R_h = R + (R - R_s)$, and $R_h = 1$, where R_s is the R^2-value of our "short regression" model presented in column (1) of Table 3 and R is the R^2-value of our main regression model presented in column (3) of Table 3. Table 5 additionally presents semi-elasticities of PPE (for an average conventional and an average organic household) as well as semi-elasticities of switching to organic farming (for an average household) that we calculated based on the bias-adjusted coefficients.[21]

Table 5: Sensitivity to omitted variables: bounds of coefficients and semi-elasticities

	$R_h = 1.25R$	$R_h = 1.50R$	$R_h = R + (R - R_s)$	$R_h = 1$	Conf. Int.
PPE	[-0.16; -0.14]	[-0.18; -0.14]	[-0.21; -0.14]	[-0.40; -0.14]	[-0.23; -0.05]
Organic	[-0.96; -0.91]	[-0.96; -0.87]	[-0.96; -0.81]	[-0.96; -0.45]	[-1.53; -0.38]
PPE * Organic	[0.20; 0.23]	[0.18; 0.23]	[0.15; 0.23]	[-0.06; 0.23]	[-0.01; 0.46]
Semi-elasticity: PPE (Convent.)	[-0.16; -0.14]	[-0.18; -0.14]	[-0.21; -0.14]	[-0.40; -0.14]	[-0.32; 0.04]
Semi-elasticity: PPE (Organic)	[0.04; 0.09]	[-0.00; 0.09]	[-0.07; 0.09]	[-0.46; 0.09]	[-0.17; 0.34]
Semi-elasticity: Organic	[-0.35; -0.34]	[-0.36; -0.34]	[-0.37; -0.34]	[-0.43; -0.34]	[-0.60; -0.09]

Notes: Column 'Conf. Int.' indicates the 99.5% confidence intervals of the estimated coefficients and semi-elasticities based on cluster-robust standard errors. See further notes below Table 3.

As none of the bounds for the coefficient of PPE or for the semi-elasticity of PPE for an average *conventional* household includes zero, we conclude that our estimated negative effect of PPE on the per-capita health expenditure of *conventional* households is robust to potential omitted-variable biases. The bounds for the semi-elasticity of PPE for an average *organic* household include zero for $R_h \geq 1.50\,R$. As the 'true' effect of PPE use on the health expenditure of *organic* households is likely zero or slightly negative, we could consider $R_h = 1.50\,R$ as a plausible scenario and conclude that an additional PPE item reduces the health expenditure of *conventional* households by around 18%, which is even larger than the estimated effect without bias adjustment. Given that none of the bounds for the coefficient of the farming method or for the semi-elasticity of switching to organic farming includes zero, we conclude that the estimated negative effect of switching to organic farming on the per-capita health expenditure is robust to potential omitted-variable biases.

[21] While the bias-adjusted semi-elasticities of PPE can be calculated based on the bias-adjusted coefficients of PPE and the interaction of PPE and the dummy variable for organic households, the calculation of the bias-adjusted semi-elasticities of switching to organic farming requires bias-adjusted coefficients of all explanatory variables. For simplicity, we assume that none of the other explanatory variables is correlated with the omitted variables so that the other coefficients do not need to be adjusted, i.e., $\hat{\beta}_h = \hat{\beta}$ and $\hat{\gamma}_h = \hat{\gamma}$ in the notation used in Appendix Section D.

As suggested by Oster (2019), we additionally check whether the bounds calculated with $R_h = 1.25R$ lie within the 99.5% confidence interval of the estimated coefficients and semi-elasticities. This is the case for all three coefficients and all three semi-elasticities even for $R_h = 1.50R$ and $R_h = R + (R - R_s)$, which further confirms the robustness of our analysis with respect to omitted variables.

4.4 Robustness checks

In order to assess the robustness of our results, we present regression results obtained with alternative specifications of our regression model (1) in Tables 6, 7, and 8. To begin with, we estimate equation (1) with an alternative transformation of the dependent variable: we use a logarithmic transformation of one plus the per-capita health expenditure, i.e., $\tilde{y}_i = \ln(1 + y_i)$, instead of the IHS-transformation to reduce the skewness of the distribution of the dependent variable without removing observations with zero values (column 1 of Table 6). In another alternative specification, we replace household size and dependency ratio by the number of household members in four different age categories (column 2 of Table 6) because a household's per-capita health expenditure may depend on the household's age composition that is not captured by its size and dependency ratio. Third, we use the total land area cultivated by the household instead of the land area cultivated with cotton as a proxy for exposure to pesticides, because farmers may use pesticides for crops other than cotton (column 3 of Table 6). Fourth, we omit training on pesticide application, bathing after pesticide application, and eating during pesticide application as explanatory variables so that the number of PPE items used is the only behavioral explanatory variable in the regression model (column 4 of Table 6). Fifth, we restrict our sample to households living in villages with organic cotton farming and villages without organic cotton farming that are similar to villages with organic cotton farming (see Section 2.1) in order to reduce potential heterogeneity in village-level characteristics between organic and conventional households (column 5 of Table 6).

As conventional and organic households may differ in many aspects (not only in those for which we include interaction terms, i.e., x_i^d), we estimate our specification with the same covariates as in the full model separately for conventional and organic households (columns 1 and 2 of Table 7). Additionally, we re-estimate equation (1) separately for conventional and organic households by using household labor and hired labor used for spraying (in hours), costs of synthetic herbicides and synthetic insecticides (only conventional households), and costs of bio-pesticides (only organic households) instead of the land area cultivated with cotton (columns 3 and 4 of Table 7) because these control variables could be more comprehensive proxies for exposure to pesticides than just the land area cultivated with cotton.[22]

The results of all regression analyses with alternative specifications presented in Tables 6 and 7 are very close to the results of our main regression model: using one additional PPE item by conventional households decreases their per-capita health expenditure by $12-17\%$ (compared to 14% in the

[22]We comment on and interpret the results regarding these covariates in Appendix Section E.

Table 6: Robustness checks with alternative specifications

	log of per-capita health expenditure	IHS of per-capita health expenditure			
	(1)	(2)	(3)	(4)	(5)
PPE	-0.11^{**} (0.05)	-0.14^{**} (0.06)	-0.14^{**} (0.06)	-0.13^{**} (0.07)	-0.17^{**} (0.07)
Organic	-0.79^{***} (0.23)	-0.94^{***} (0.27)	-0.77^{*} (0.42)	-0.82^{***} (0.23)	-1.08^{***} (0.30)
Gender (male)	−0.02 (0.15)	−0.02 (0.17)	−0.03 (0.16)	−0.06 (0.17)	0.02 (0.20)
Age of household head	0.002 (0.002)	0.003 (0.004)	0.004 (0.003)	0.003 (0.004)	0.003 (0.003)
Years of education	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)	0.02 (0.02)	0.01 (0.02)
Experience in cotton production	−0.004 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
Household size	-0.03^{**} (0.01)		-0.04^{**} (0.02)	-0.04^{*} (0.02)	-0.04^{**} (0.02)
Dependency ratio	0.23 (0.19)		0.29 (0.23)	0.32 (0.26)	0.37 (0.23)
Number aged 0-14		−0.002 (0.01)			
Number aged 15-35		-0.07^{**} (0.03)			
Number aged 36-65		−0.06 (0.04)			
Number aged ≥ 66		0.05 (0.11)			
log(Household assets)	0.22^{***} (0.04)	0.27^{***} (0.05)	0.24^{***} (0.04)	0.28^{***} (0.05)	0.28^{***} (0.06)
Water deprivation	0.05 (0.08)	0.06 (0.09)	0.06 (0.09)	0.06 (0.08)	0.08 (0.12)
log(Land cultivated with cotton)	0.11 (0.07)	0.14^{*} (0.08)		0.16^{**} (0.08)	0.09 (0.09)
log(Total land cultivated)			0.25^{***} (0.08)		
Training in pesticide application	0.29^{**} (0.12)	0.35^{**} (0.14)	0.35^{***} (0.13)		0.42^{***} (0.13)
Bathing after pesticide application	0.15 (0.12)	0.17 (0.14)	0.20 (0.15)		0.15 (0.16)
Eating during pesticide application	0.36 (0.23)	0.43^{*} (0.25)	0.44^{*} (0.25)		0.52^{*} (0.29)
Health attitude	-0.11^{***} (0.03)	-0.13^{***} (0.03)	-0.13^{***} (0.04)	-0.11^{***} (0.04)	-0.12^{***} (0.04)
PPE * Organic	0.19^{***} (0.05)	0.23^{***} (0.07)	0.23^{***} (0.07)	0.31^{***} (0.03)	0.26^{***} (0.06)
Organic * log(Land cultivated with cotton)	-0.09^{**} (0.04)	-0.10^{**} (0.05)		−0.10 (0.07)	−0.05 (0.04)
Organic * log(Total land cultivated)			−0.14 (0.16)		
Organic * Training in pesticide application	−0.20 (0.18)	−0.26 (0.21)	−0.26 (0.20)		−0.31 (0.19)
Organic * Bathing after pesticide application	0.32 (0.30)	0.39 (0.38)	0.41 (0.36)		0.40 (0.40)
Organic * Eating during pesticide application	−0.36 (0.25)	−0.41 (0.28)	−0.42 (0.28)		-0.56^{*} (0.31)
Constant	−0.63 (0.45)	−0.64 (0.50)	−0.85 (0.53)	−0.63 (0.61)	−0.75 (0.70)
Arrondissement-fixed effects	Yes	Yes	Yes	Yes	Yes
Semi-elasticity: PPE (Conventional)	$-0.12\ (0.06)^{**}$	$-0.14\ (0.06)^{**}$	$-0.14\ (0.06)^{**}$	$-0.13\ (0.07)^{**}$	$-0.17\ (0.07)^{**}$
Semi-elasticity: PPE (Organic)	0.08 (0.08)	0.09 (0.09)	0.09 (0.09)	$0.18\ (0.06)^{***}$	0.09 (0.09)
Semi-elasticity: Organic	$-0.32\ (0.17)^{*}$	$-0.33\ (0.12)^{***}$	$-0.35\ (0.10)^{***}$	$-0.22\ (0.10)^{**}$	$-0.34\ (0.13)^{**}$
Log-likelihood	−1656.65	−1847.04	−1845.35	−1868.95	−1506.37
Akaike's Inf. Crit.	3383.29	3768.07	3760.70	3795.90	3072.74
Bayesian Inf. Crit.	3561.56	3956.53	3938.97	3943.61	3219.37
Observations	1204	1204	1204	1204	980
R squared	0.25	0.25	0.26	0.23	0.27

Notes: The regression results in column (5) are only based on observations from villages with organic cotton production and villages without organic cotton production that are similar to villages with organic cotton production. As the regression analysis presented in column (1) has a different dependent variable and the regression analysis presented in column (5) has a different number of observations than the other regression analyses, the log-likelihood values, Akaike's Information Criteria, and Bayesian Information Criteria in columns (1) and (5) are not comparable to the corresponding values in the other columns of this table and of Table 3. See further notes below Table 3.

Table 7: Robustness checks with separate estimations for conventional and organic households

	IHS of per-capita health expenditure			
	Conventional	Organic	Conventional	Organic
	(1)	(2)	(3)	(4)
PPE	−0.13** (0.07)	0.07 (0.08)	−0.14** (0.07)	0.05 (0.08)
Gender (male)	−0.04 (0.13)	−0.04 (0.35)	−0.03 (0.12)	−0.06 (0.35)
Age of household head	0.01 (0.004)	−0.003 (0.01)	0.01 (0.003)	−0.002 (0.01)
Years of education	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)
Experience in cotton production	−0.01 (0.01)	−0.01 (0.02)	−0.01 (0.01)	−0.01 (0.02)
Household size	−0.05*** (0.02)	0.02 (0.04)	−0.05*** (0.01)	−0.005 (0.03)
Dependency ratio	0.35* (0.20)	−0.002 (0.72)	0.40** (0.18)	0.24 (0.56)
log(Household assets)	0.25*** (0.05)	0.26*** (0.06)	0.24*** (0.05)	0.28*** (0.06)
Water deprivation	0.08 (0.10)	0.03 (0.10)	0.07 (0.10)	0.02 (0.11)
log(Land cultivated with cotton)	0.16** (0.08)	0.003 (0.08)		
log(Pesticide application by household labor)			0.23*** (0.07)	0.05 (0.07)
asinh(Pesticide application by hired labor)			−0.09* (0.05)	−0.41*** (0.09)
asinh(Costs of herbicides)			0.04 (0.04)	
asinh(Costs of insecticides)			−0.04 (0.06)	
asinh(Costs of biopesticides)				0.02 (0.05)
Training in pesticide application	0.33** (0.14)	0.14 (0.27)	0.28** (0.14)	0.01 (0.18)
Bathing after pesticide application	0.15 (0.15)	0.56* (0.31)	0.16 (0.15)	0.61* (0.33)
Eating during pesticide application	0.45* (0.25)	−0.16 (0.14)	0.37** (0.18)	−0.19 (0.17)
Health attitude	−0.14*** (0.04)	−0.09 (0.15)	−0.13*** (0.03)	−0.11 (0.14)
Constant	−0.42 (0.53)	−1.65 (1.10)	−0.93 (0.58)	−1.96** (0.83)
Arrondissement-fixed effects	Yes	Yes	Yes	Yes
Semi-elasticity: PPE	−0.13 (0.07)**	0.08 (0.08)	−0.14 (0.07)**	0.05 (0.08)
Log-likelihood	−1545.11	−294.19	−1530.10	−285.08
Akaike's Inf. Crit.	3148.22	632.37	3124.21	618.16
Bayesian Inf. Crit.	3290.58	705.26	3281.26	697.44
Observations	1001	203	1000	201
R squared.	0.24	0.25	0.26	0.28

Notes: 'Semi-elasticity: PPE' indicates the semi-elasticity of PPE calculated for an average conventional household (columns 1 and 3) or an average organic household (columns 2 and 4). The regression analyses in columns 3 and 4 have fewer observations than those in columns 1 and 2, respectively, because there are missing values in some of the explanatory variables (see Table 1). See further notes below Table 3.

main regression model). Furthermore, PPE use does not significantly affect the per-capita health expenditure of organic households except for the regression model without other behavioral explanatory variables (column 4 of Table 6),[23] and switching to organic cotton farming reduces per-capita health expenditure by $22-35\%$ (compared to 34% in the main regression model). Hence, we conclude that our regression results are very robust to changes in the model specification.

As final robustness checks, we use instrumental-variable estimations. Column 1 of Table 8 presents the results of the full model specification as defined in equation (1). In this specification, we treat the number of PPE items (P_i), the dummy variable indicating organic farming (D_i), and all interaction terms that involve at least one of these variables ($P_i D_i$, $x_i^d D_i$) as endogenous regressors. We use the three-stage IV approach suggested by Wooldridge (2010, p. 937–942) because—in contrast to the classical 2-stage least-squares (2SLS) approach—it takes into account that one of the endogenous regressors, the dummy variable indicating organic farming (D_i), is a binary variable. In the first stage, we conduct a probit regression of the dummy variable indicating organic farming (D_i) on all exogenous explanatory variables x_i and the exposure to organic farming ($\bar{D}_i$) defined as the proportion of organic households in each village, which we use as instrument for the participation in organic farming D_i (see, e.g., Sellare et al., 2020). Then, we conduct a classical 2SLS regression with the following instrumental variables: the social norm of PPE use by peers in the village ($\bar{P}_i$) defined as the average number of PPE items used by farmers with the same cotton farming method (i.e., organic or conventional) in the same village excluding the household itself (see, e.g., Tabe-Ojong et al., 2021),[24] the squared value of this variable ($\bar{P}_i^2$) to take into account non-linearity between $\bar{P}_i$ and P_i (see Figure I.1 in Appendix Section I), the probability of participation in organic farming predicted by the first-stage probit model ($\hat{D}_i$), interaction terms between these variables ($\bar{P}_i \hat{D}_i$, $\bar{P}_i^2 \hat{D}_i$), and interaction terms between the predicted probabilities of participation in organic farming and the covariates x_i^d ($x_i^d \hat{D}_i$). As the endogenous interaction terms make this IV regression complex and vulnerable to various types of misspecification, we also use the classical 2SLS method to estimate the effect of PPE on per-capita health expenditure separately for conventional and organic households (columns 2 and 3 of Table 8). In these 2SLS regression analyses, we have a single endogenous regressor (P_i), and we use the social norm of PPE use by peers in the village ($\bar{P}_i$) and its squared value ($\bar{P}_i^2$) as instrumental variables.

Statistical tests clearly reject that our instrumental variables are "weak" in the regression analysis involving all households and the regression analysis involving only conventional households.

[23]The regression model without other behavioral explanatory variables finds that PPE use substantially and statistically significantly increases per-capita health expenditure of organic households. Given that it can be excluded that PPE use has a positive causal effect on per-capita health expenditure in reality, we can conclude that it is important to control for these other behavioral variables in our regression analysis.

[24]We calculate variable $\bar{P}_i$ before removing non-certified organic farmers in order to have a sufficient number of peers for organic farmers. However, in three villages there is only a single organic household in our data set so that variable $\bar{P}_i$ cannot be calculated for these three households. Hence, these three organic households cannot be included in the regression analyses with instrumental variables. The proportion of organic households in each village and the social norm of PPE use by peers in the village that we use as instruments are in line with Wuepper et al. (2018), Magnan et al. (2015), and Krishnan and Patnam (2014), who show how learning from neighbors is important for decision making regarding behavioral change and technology adoption. Similar instruments are used by Mason and Smale (2013) and Smale and Mason (2014).

Table 8: Robustness checks with instrumental variable regression

	IHS of per-capita health expenditure		
	Full model (with interaction term)	Only Conventional	Only Organic
	(1)	(2)	(3)
PPE	-0.42^{**} (0.20)	-0.43^{**} (0.19)	1.58^{*} (0.83)
Organic	-2.57^{***} (0.95)		
Gender (male)	0.18 (0.22)	0.07 (0.20)	0.51 (0.56)
Age of household head	0.004 (0.01)	0.004 (0.01)	−0.01 (0.01)
Years of education	0.0002 (0.02)	0.02 (0.02)	−0.07 (0.06)
Experience in cotton production	−0.01 (0.01)	−0.001 (0.01)	0.01 (0.02)
Household size	-0.04^{**} (0.02)	-0.03^{*} (0.01)	0.01 (0.06)
Dependency ratio	0.46^{*} (0.26)	0.31 (0.23)	0.76 (0.88)
log(Household assets)	0.25^{***} (0.05)	0.30^{***} (0.05)	−0.04 (0.24)
Water deprivation	0.02 (0.10)	0.04 (0.09)	−0.29 (0.35)
log(Land cultivated with cotton)	0.25^{***} (0.08)		
Training in pesticide application	0.48^{***} (0.16)		
Bathing after pesticide application	0.19^{*} (0.10)		
Eating during pesticide application	0.31^{**} (0.14)		
Health attitude	-0.09^{***} (0.03)	-0.10^{***} (0.02)	−0.52 (0.38)
PPE * Organic	2.01^{**} (0.93)		
Organic * log(Land cultivated with cotton)	0.05 (0.25)		
Organic * Training in pesticide application	-1.54^{***} (0.56)		
Organic * Bathing after pesticide application	−0.67 (0.80)		
Organic * Eating during pesticide application	1.25 (0.95)		
Constant	−0.50 (0.63)	−0.49 (0.62)	−0.004 (2.57)
Arrondissement-fixed effects	Yes	Yes	Yes
Semi-elasticity: PPE (Conventional)	-0.42 $(0.20)^{**}$	-0.43 $(0.19)^{**}$	
Semi-elasticity: PPE (Organic)	1.61 $(0.87)^{*}$		1.59 $(0.84)^{*}$
Semi-elasticity: Organic	3.50 (2.69)		
Weak instruments: PPE	6.37^{***}	14.37^{***}	1.59
Weak instruments: Organic	156.79^{***}		
Weak instruments: PPE * Organic	50.86^{***}		
Weak instruments: Organic * log(Land cultivated with cotton)	163.80^{***}		
Weak instruments: Organic * Training in pesticide application	347.63^{***}		
Weak instruments: Organic * Bathing after pesticide application	175.67^{***}		
Weak instruments: Organic * Eating during pesticide application	712.62^{***}		
Wu-Hausman test	2.70^{***}	2.93^{*}	6.89^{***}
Sargan test for overidentifiction	0.69	3.16^{*}	0.01
Log-likelihood	−2052.25	−1612.81	−407.38
Akaike's Inf. Crit.	4174.50	3275.62	848.76
Bayesian Inf. Crit.	4352.68	3398.34	904.83
Observations	1201	1001	200
R squared	−0.06	0.13	−1.49

Note: See notes below Table 3.

However, we could not find strong and plausibly exogenous instrumental variables for the regression analysis involving only organic households. Perhaps caused by too weak instruments for the number of PPE items used by organic farmers, the R^2-values of the regression analyses with all households and with organic households only are both negative, which casts some doubt on the suitability of these model specifications.[25] However, the 2SLS regression analysis with only conventional households has a positive R^2-value and generally reasonable results. This regression analysis confirms our main result that PPE use vastly reduces per-capita health expenditure of conventional households. Furthermore, a Wu-Hausman test for this regression analysis does not reject our OLS regression at 5% significance level, which supports the reliability of our selection-on-observables identification strategy.

5 Conclusion

Using cross-sectional data from 1,204 households in Benin that produce conventional or organic cotton, we investigate the effect of using personal protective equipment (PPE) during the spraying of pesticides on the health of these farmers and their household members, as proxied by the households' per-capita health expenditure. Our empirical analysis is based on a selection-on-observables identification strategy. We control for variables that are likely correlated with both health expenditure and PPE use to bring our analyzed *ceteris paribus* relationships as close to causal effects as possible. Several robustness checks, including instrumental-variable regression, accounting for effects of omitted variables, and genetic matching, confirm our results.

Our results show that PPE use while spraying pesticides significantly reduces detrimental health effects of synthetic pesticides: each additional PPE item reduces the per-capita health expenditure of conventional farmers by around 14%. As we do not find this effect for organic cotton producers, we conclude that bio-pesticides have no or significantly fewer detrimental effects on health than synthetic pesticides, even if they are applied with little or no protective equipment. When conventional cotton producers use four or more PPE items while spraying pesticides, they have a similar per-capita health expenditure as organic cotton producers, which suggests that appropriately handling pesticides, such as using PPE, can substantially reduce the detrimental effects of synthetic pesticides on the health of conventional cotton farmers and their household members. As most farmers wear only very little PPE while spraying pesticides, most households would substantially reduce the detrimental health effects of pesticides by switching from conventional to organic cotton farming as indicated by our estimated reduction of approximately 34% in the per-capita health expenditure for an average household.

However, our results only take into account the health of household members; they do not consider the health of hired laborers or other people who are otherwise (e.g., through lower contamination of agricultural products, fish, and water with pesticide residues) affected by the handling or spraying of pesticides (see, e.g., Feola and Binder, 2010; Damalas and Abdollahzadeh, 2016). Hence, the

[25] We tried out various sets of potential instrumental variables but we did not find a specification that provided less problematic results.

social benefits of using PPE, appropriately handling pesticides, and switching to organic farming for the health of the entire population are expected to be even larger than our estimated effects on the health of the household members. Furthermore, at least some of these measures would also have environmental benefits.

Moreover, as our study is based on a cross-sectional data set from a single (cotton) growing season, our results can only take into account long-term effects of pesticides on health (see, e.g., Maroni et al., 2006) if farmers kept their use of pesticides and PPE more or less constant over the past several growing seasons. We partly addressed this potential problem by excluding farm households that switched from conventional to organic farming less than three years before the survey. A study based on longitudinal data would enable the investigation of long-term health effects of pesticides in a more appropriate way.

Although our measure of farmers' health, i.e., per-capita health expenditure, has some desirable traits such as being inexpensive to observe and taking into account health problems that are difficult to prove as having been caused by contamination with pesticides, it also has some weaknesses. For instance, as the cotton farmers in our data set are subsistence farmers, a part of the negative effect on per-capita health expenditure of switching to organic farming could be caused by a reduction in pesticide-residue contamination of the self-produced food consumed by the household, rather than through the absence of contamination with synthetic pesticides during crop spraying. However, as households do not consume the produced cotton and even conventional households apply only very little pesticide to food crops, this effect is assumed to be negligible. Another potential problem could be that households in our data set are very poor and their members may not always visit health care facilities even when they are sick because they cannot afford medical expenses. As we control for wealth in our analyses (and indeed find a substantial positive association between wealth and per-capita health expenditure), this potential problem does not affect our estimates of the *relative* effects of using PPE and of switching to organic farming on the plausible assumption that a lack of resources reduces health-care visits due to pesticide-related health problems in the same way as it reduces health-care visits due to health problems that are unrelated to contamination with pesticides. However, the reduced use of health services results in an under-estimation of the *absolute* effects on farmers' health of using PPE and switching to organic farming. Finally, as those household members who predominantly handle and spray pesticides are exposed to a greater extent to pesticides than other household members, our estimates of the effects on per-capital health expenditure indicate the average of the effects on all household members, although it can be presumed that the effects on those household members who predominantly handle and spray pesticides are much larger and the effects on the other household members are much smaller than indicated by our estimates. Hence, when interpreting our estimation results, one needs to consider these potential weaknesses in our measure of farmers' health.

Despite these potential weaknesses, our study clearly indicates that stakeholders such as politicians, extension officers, pesticide producers and traders, farmers organizations, and other NGOs could contribute to improving the health of cotton farmers by supporting measures that substantially increase PPE use or promote the switch to organic cotton farming. Future research could, thus, investigate the effectiveness of various measures such as policies, regulations, programs, and information campaigns that aim to increase PPE use while spraying pesticides or the adoption of organic farming practices.

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Appendix

A Pesticide handling and human health

Pest control measures aim to reduce the incidence of harmful pests that decrease yields, cause pre- and post-harvest damage, or threaten the health of consumers (Sheahan et al., 2017). One of the most frequently used pest control measures is the application of pesticides. Pesticides can increase farmers' revenues from selling agricultural output or decrease their labor costs (Gianessi and Williams, 2011) and, thus, improve profitability if the potential gains from protecting the crops outweigh the costs of applying the pesticides. In many cases, the application of pesticides is highly profitable so that most of today's agricultural production systems crucially rely on their use.

However, the link between pesticides and both acute and long-term illnesses is well known (Crissman et al., 1994; Wilson and Tisdell, 2001; Maroni et al., 2006). An extensive body of empirical literature (e.g., Harper and Zilberman, 1992; Weisenburger, 1993; Antle and Capalbo, 1994; Antle and Pingali, 1994; Cole et al., 2000; Sunding and Zivin, 2000; Cole et al., 2002; Maumbe and Swinton, 2003; Cooper and Dobson, 2007; Asfaw et al., 2010; Okello and Swinton, 2010; Waterfield and Zilberman, 2012; Atreya et al., 2012; Macharia et al., 2013a; Sheahan et al., 2017) investigates how pesticides affect the health of farmers. Several studies (e.g., Antle and Capalbo, 1994; Murphy et al., 2000; Maumbe and Swinton, 2003) show that exposure to pesticides can result in acute symptoms, such as headache, dizziness, muscular twitching, skin irritation, and respiratory discomfort. Murphy et al. (2000) find that female farmers in Indonesia who sprayed pesticides had significantly more adverse symptoms than comparable farmers who did not spray pesticides. Maumbe and Swinton (2003) show that more than half of the cotton growers in Zimbabwe had skin irritations, more than a quarter of them had eye irritations, and about 10% of them experienced stomach poisoning. Pesticides have the potential to not only cause acute poisonings but can also produce long-term adverse health effects, such as cancer and reproductive dysfunctions (Maroni et al., 2006). A cohort study from China shows that pesticide exposure adversely affects blood cells, the liver, and the peripheral nervous system (Hu et al., 2015). Sheahan et al. (2017) do not distinguish between acute and long-term effects but find that in agricultural households in four Sub-Saharan countries, pesticide use is associated with higher health expenditures and more time lost from work due to sickness.

Contaminations with pesticides entail both private and public costs. Pesticide-related health care costs vary across countries. For example, Pimentel and Burgess (2014) estimate that the yearly public health costs of pesticide use in the USA amount to 1.1 billion USD. A study from India (Devi, 2007) estimates annual health care costs of pesticide use to be around 36 USD per applicator. In Brazil, the costs of acute poisoning are estimated at 64% of the benefits of using herbicides and insecticides in maize farming (Soares and de Souza Porto, 2009). The cost estimates depend not only on the amounts of pesticides that are applied and the measures that are taken to reduce contamination but also on whether the studies focus on acute illnesses or on long-term chronic illnesses.

Several factors can affect exposure during pesticide handling. In particular, different formulations carry different risks of contamination. While liquids carry a higher risk of splashing and spillage, resulting in direct or indirect skin contact through clothing, solids may generate dust and cause skin, eye, or respiratory damage (Damalas and Eleftherohorinos, 2011). Chemical volatility of the product also depends on weather conditions, such as air temperature and humidity, at the time of application. For example, wind increases spray drift and resultant exposure of the applicator, while low relative humidity and high temperature cause more rapid evaporation of spray droplets between the spray nozzle and the target than high relative humidity and low temperature (Damalas and Eleftherohorinos, 2011). The frequency and duration of a person's pesticide handling also affect his/her exposure to pesticides (see, e.g., Sheahan et al., 2017). Finally, PPE use can reduce farmers' contamination with pesticides.

Studies in a number of developing countries indicate that farmers have limited knowledge about the health hazards of pesticides and the benefits of using PPE (Mekonnen and Agonafir, 2002; Feola and Binder, 2010; Okoffo et al., 2016; Zapata Diomedi and Nauges, 2016). This knowledge is related to socio-demographic variables (e.g., age, education, gender), social norms (i.e., the desire to behave like others), past health issues, and risk perceptions (Mekonnen and Agonafir, 2002; Feola and Binder, 2010; Okoffo et al., 2016; Zapata Diomedi and Nauges, 2016). For instance, Okoffo et al. (2016) find that PPE use by cocoa farmers in Ghana is positively related to farming experience, age, receiving extension service, availability of a shop in the village that sells pesticides, farm size, and education. Mrema et al. (2017) show that reduced educational opportunities put women at an even greater risk of experiencing adverse effects of pesticides than men in the pesticide-intensive horticultural sector in Tanzania. The analysis by Zapata Diomedi and Nauges (2016) shows that general education and training in the handling of pesticides largely determine to which extent smallholder coffee farmers in Papua New Guinea use PPE and how they dispose pesticide containers. Asfaw et al. (2009) find that certification of good agricultural practices, including pesticide handling practices, is positively related to the use of safer types of pesticides by small-scale vegetable producers in Kenya. These findings are supported by a series of studies that show that providing training to farmers can increase knowledge about pesticide-related hazards and promote safer pesticide handling practices (e.g., Hruska and Corriols, 2002; Feder et al., 2004). However, even if farmers are aware of pesticide-related risks, they frequently do not handle pesticides with care, and they do not regularly use PPE (Antle et al., 1998; Isin and Yildirim, 2007; Okoffo et al., 2016).

There is little empirical evidence of the effect of pesticide handling practices and PPE use on farmers' pesticide-related health problems. Midingoyi et al. (2019) report that adopting integrated pest management (IPM) practices reduces the detrimental effect of pesticides on the health of mango farmers in Kenya but this study only investigates the quantity and toxicity of the pesticides that farmers apply; neither does it use a direct nor an indirect measure of human health. The analysis of small-scale vegetable producers in Kenya by Asfaw et al. (2010) shows that adopting European Union private-sector standards, including standards for safer pesticide handling, is associated with smaller numbers of pesticide-ascribed incidences of acute illness symptoms and with lower costs of treating these illnesses. Okello and Swinton (2010) find that complying with developed-country pesticide standards improves the health of green bean farmers in Kenya and that changing clothing and bathing after spraying is associated with lower costs of treating pesticide-related illnesses, which could be explained by a reduced duration of skin contact with pesticides.

B List of village-level characteristics used for selecting villages

Table B.1 presents the village-level variables that we used in the genetic matching for selecting villages without organic cotton farming that are similar to villages with organic cotton farming and in the optimization procedure for selecting the third group of villages so that the village-level characteristics of all selected villages are similar to those of all villages in the respective district. We used different sets of variables for each of the three districts, because in one or two of the three districts, some variables were not available, had a non-negligible number of missing values, were almost perfectly correlated with other variables, had almost no variation, or had no significant differences between villages with and without organic cotton farming.

Table B.1: Village-level characteristics used for selecting villages

Variables	Kandi	Pehunco	Glazoué
importance of income from cotton in household income (1=very high, 2=high, 3=low)	X	X	X
soil fertility (1=very fertile, 2=fertile, 3=less fertile)	X	X	X
average children schooling rate in the village (%)	X		
distance to tarred road (km)	X	X	X
distance to chief town of the district (km)			X
distance to chief town of the arrondissement (km)	X		X
distance to food market (km)			X
distance to cotton market (km)	X		
conventional cotton production (tons)	X		X
number of conventional cotton farmers	X		
availability of land for agriculture (1=largely available, 2=available, 3=less available)	X	X	X
average living standard in the village (1=very rich, 2=rich, 3=poor)			X
connection to the electricity grid (Yes/No)			X
existence of a health center (Yes/No)	X	X	X
existence of a school (Yes/No)			X
proportion of farmers who use draught animals for land preparation and other farming activities (%)	X	X	X
proportion of farmers who use a tractor for land preparation and other farming activities (%)	X		

C Questionnaires

Our survey of cotton-farming households and those of their members who were responsible for cotton production was conducted with the KoBoCollect software (`https://www.kobotoolbox.org`). We exported the household-level questionnaire and the producer-level questionnaire that we used in our survey from the KoBoCollect software as PDF files and as spreadsheet files. These files have the Digital Object Identifier (DOI) “10.5281/zenodo.5008811” and are publicly available at `http://doi.org/10.5281/zenodo.5008811` (**?**). Compared to the PDF files, the spreadsheet files provide additional information such as the French translations of the questions, the types of the obtained variables, restrictions on the entered values, information about questions that should be skipped in case of certain responses to previous questions, etc.

D Sensitivity to omitted variables

We apply the approach suggested by Oster (2019) to assess the sensitivity of our analysis to omitted variables. This approach uses the (observable) relationships between the explanatory variable(s) of interest (i.e., in our empirical application P_i and D_i) and other explanatory variables to recover the (unobservable) relationships between the explanatory variable(s) of interest and omitted explanatory variables. In order to do this, we conduct a so-called “short regression” by using only the main variables of interest as explanatory variables:

$$\tilde{y}_i = \beta_{s0} + \delta_s D_i + \theta_s P_i + \lambda_s P_i D_i + \varepsilon_{si}, \tag{D.1}$$

where the subscript s indicates that the parameters and the error term are part of this “short regression” model. We denote a set of unobserved variables that are omitted in our regression model (1) by U_i so that a hypothetical regression specification with all relevant unobserved variables U_i that would give unbiased estimates is specified as:

$$\tilde{y}_i = \beta_{h0} + \delta_h D_i + \theta_h P_i + \lambda_h P_i D_i + \beta_h' x_i + \gamma_h' x_i^d D_i + \psi_h' U_i + \varepsilon_{hi}, \tag{D.2}$$

where ψ_h is a vector of parameters and the subscript h indicates that the parameters and the error term are part of this hypothetical regression model. Under some assumptions outlined by Oster (2019), we can obtain bias-adjusted estimates of parameters δ, θ, and λ by:

$$\hat{\mu}_h = \hat{\mu} - \rho \left[\hat{\mu}_s - \hat{\mu}\right] \frac{R_h - R}{R - R_s}, \tag{D.3}$$

where $\hat{\mu}_h \in \left\{\hat{\delta}_h, \hat{\theta}_h, \hat{\lambda}_h\right\}$ is a bias-adjusted coefficient that corresponds to equation (D.2), $\hat{\mu} \in \left\{\hat{\delta}, \hat{\theta}, \hat{\lambda}\right\}$ is an estimate of parameter δ, θ, or λ obtained by our actual regression model (1), $\hat{\mu}_s \in \left\{\hat{\delta}_s, \hat{\theta}_s, \hat{\lambda}_s\right\}$ is an estimate of parameter δ_s, θ_s, or λ_s obtained by our “short regression” model (D.1), R_h is the (assumed) R^2-value of the hypothetical regression model (D.2), R is the R^2-value of our actual regression model (1), R_s is the R^2-value of our "short regression" model (D.1), and ρ is the (assumed) value of the coefficient of proportionality with $\rho\left(\sigma_{1P}/\sigma_1^2\right) = \left(\sigma_{2P}/\sigma_2^2\right)$, $\sigma_{1P} = \mathrm{COV}\left(W_{1i}, P_i\right)$, $\sigma_1^2 = \mathrm{VAR}\left(W_{1i}\right)$, $\sigma_{2P} = \mathrm{COV}\left(W_{2i}, P_i\right)$, $\sigma_2^2 = \mathrm{VAR}\left(W_{2i}\right)$, $W_{1i} = \beta_h' x_i + \gamma_h' x_i^d D_i$ and $W_{2i} = \psi_h' U_i$.

We assume an equal selection of observables and unobservables so that the coefficient of proportionality is $\rho = 1$, and we follow Oster (2019) and assume different values for R_h, i.e., the R^2-value of the hypothetical regression (D.2). We assume $R_h = 1.25\,R$ and $R_h = 1.50\,R$ as suggested by Oster (2019), $R_h = R + (R - R_s)$ as suggested by Bellows and Miguel (2009), and $R_h = 1$ as hypothesized for no statistical noise in the hypothetical regression with all omitted variables used as explanatory variables (i.e., $\varepsilon_{hi} = 0\,\forall\, i$). We define the bounding set as $\Delta_h = [\hat{\mu}_h, \hat{\mu}]$. If a bounding set Δ_h excludes zero (i.e., $\hat{\mu}_h$ and $\hat{\mu}$ have the same sign), we can claim that the detected effect is robust to omitted-variable biases and that a potentially found *ceteris paribus* relationship can be interpreted as causal effect.

E Interpretation of further results presented in Table 7

In the regression analyses presented in columns 3 and 4 of Table 7, we do not find a statistically significant association between the quantities of any type of pesticide (proxied by their costs) and per-capita health expenditure. However, for conventional households, we find a clear positive association between household labor used for spraying and per-capita health expenditure and a clear negative association between hired labor used for spraying and per-capita health expenditure. The positive estimate for household labor is expected because it clearly proxies exposure of household members to pesticides. The negative estimate for hired labor could perhaps indicate that the spraying activities that involve a higher risk of getting contaminated with pesticides are delegated to hired laborers so that household members get less contaminated in the given time that they use for spraying. However, this explanation is mere speculation and would be an interesting topic for future research. An unexpected finding was the statistically significant negative association between hired labor used for spraying and per-capita health expenditure for organic households; this needs further investigation.

F Standard errors of semi-elasticities

F.1 Semi-elasticities of PPE

We apply the Delta method to calculate approximate standard errors of the semi-elasticity of PPE (as defined at the end of Section 3.1):

$$se\left(\tilde{\varepsilon}_{(y_i/P_i)}\right) = \sqrt{\frac{\partial \tilde{\varepsilon}_{(y_i/P_i)}}{\partial\left(\hat{\theta},\hat{\lambda}\right)} \text{COV}\begin{pmatrix} \hat{\theta} \\ \hat{\lambda} \end{pmatrix} \frac{\partial \tilde{\varepsilon}_{(y_i/P_i)}}{\partial \begin{pmatrix} \hat{\theta} \\ \hat{\lambda} \end{pmatrix}}} \tag{F.1}$$

with:

$$\frac{\partial \tilde{\varepsilon}_{(y_i/P_i)}}{\partial \begin{pmatrix} \hat{\theta} \\ \hat{\lambda} \end{pmatrix}} = \begin{pmatrix} \sqrt{y_i^2+1}/y_i \\ D_i\sqrt{y_i^2+1}/y_i \end{pmatrix}. \tag{F.2}$$

For the robustness check with a log-transformed dependent variable, i.e., $\tilde{y}_i = \ln(y_i+1)$, we calculate the semi-elasticity of PPE by:

$$\tilde{\varepsilon}_{(y_i/P_i)} = \left(\hat{\theta}+\hat{\lambda}D_i\right)\frac{y_i+1}{y_i} \tag{F.3}$$

so that the Jacobian for calculating its standard error is:

$$\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial \begin{pmatrix} \hat{\theta} \\ \hat{\lambda} \end{pmatrix}} = \begin{pmatrix} 1 \\ D_i \end{pmatrix}\frac{y_i+1}{y_i}. \tag{F.4}$$

F.2 Semi-elasticities of switching to organic farming

We apply the Delta method to calculate approximate standard errors of the semi-elasticity of organic farming (as defined in equation (3)):

$$se\left(\tilde{\varepsilon}_{(y_i/D_i)}\right) = \sqrt{\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial\left(\hat{\delta},\hat{\lambda},\hat{\gamma}'\right)} \text{COV}\begin{pmatrix} \hat{\delta} \\ \hat{\lambda} \\ \hat{\gamma} \end{pmatrix} \frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial \begin{pmatrix} \hat{\delta} \\ \hat{\lambda} \\ \hat{\gamma} \end{pmatrix}}} \tag{F.5}$$

with:

$$\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial \begin{pmatrix} \hat{\delta} \\ \hat{\lambda} \\ \hat{\gamma} \end{pmatrix}} = \begin{pmatrix} \frac{(1-D_i)\cosh(\zeta_1)\sinh(\zeta_2) - D_i \sinh(\zeta_1)\cosh(\zeta_2)}{\sinh(\zeta_2)^2} \\ \frac{(1-D_i)P_i\cosh(\zeta_1)\sinh(\zeta_2) - D_iP_i \sinh(\zeta_1)\cosh(\zeta_2)}{\sinh(\zeta_2)^2} \\ \frac{(1-D_i)x_i^d\cosh(\zeta_1)\sinh(\zeta_2) - D_ix_i^d \sinh(\zeta_1)\cosh(\zeta_2)}{\sinh(\zeta_2)^2} \end{pmatrix} \tag{F.6}$$

$$= \begin{pmatrix} 1 \\ P_i \\ x_i^d \end{pmatrix} \frac{(1-D_i)\cosh(\zeta_1)\sinh(\zeta_2) - D_i \sinh(\zeta_1)\cosh(\zeta_2)}{\sinh(\zeta_2)^2} \tag{F.7}$$

and

$$\zeta_1 = \tilde{y}_i + \left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right)(1-D_i) \tag{F.8}$$

$$\zeta_2 = \tilde{y}_i - \left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right)D_i \tag{F.9}$$

so that $\tilde{\varepsilon}_{(y_i/D_i)} = \sinh(\zeta_1)/\sinh(\zeta_2) - 1$.

For the robustness check with a log-transformed dependent variable, $\tilde{y}_i = \ln(y_i+1)$, we calculate the approximate semi-elasticity of switching to organic farming by:[26]

$$\tilde{\varepsilon}_{(y_i/D_i)} \approx \left(\exp\left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right) - 1\right)\frac{y_i+1}{y_i} \tag{F.10}$$

so that the Jacobian for calculating its standard error is:

$$\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial \begin{pmatrix} \hat{\delta} \\ \hat{\lambda} \\ \hat{\gamma} \end{pmatrix}} = \begin{pmatrix} \exp\left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right) \\ \exp\left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right)P_i \\ \exp\left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right)x_i^d \end{pmatrix}\frac{y_i+1}{y_i} \tag{F.11}$$

$$= \begin{pmatrix} 1 \\ P_i \\ x_i^d \end{pmatrix}\exp\left(\hat{\delta} + \hat{\lambda}P_i + \hat{\gamma}x_i^d\right)\frac{y_i+1}{y_i}. \tag{F.12}$$

[26] We approximate $\exp(\beta_0 + \theta\, P_i + \beta'\, x_i)\,/\,(\exp(\beta_0 + \theta\, P_i + \beta'\, x_i) - 1)$ by $(y_i+1)\,/\,y_i$ based on the assumption $D_i = 0$. When we apply this approximate equation to calculate the semi-elasticity of switching to organic farming at the sample mean values, we use the mean health expenditure of all conventional households, i.e., households with $D_i = 0$ (instead of the mean health expenditure of all households in the sample) as value for y_i in order to take this approximation into account.

G Genetic Matching

We use genetic one-to-one nearest-neighbor matching with replacement (Diamond and Sekhon, 2013) as an additional method to investigate the effect of switching from conventional to organic cotton farming on per-capita health expenditure. Initially, we tried to match organic and conventional households on all covariates x_i but it turned out to be impossible to achieve reasonable balancing simultaneously for all covariates. Since balancing needs to be achieved only for the variables that affect the outcome (per-capita health expenditure in our empirical application), we use only those covariates for the matching that are statistically significant at 10% level in at least one of our three main regression models (columns 2–4 of Table 3). Furthermore, as there are no organic households in half of the arrondissements (and only five of fourteen arrondissements have more than two organic households in our data set), we do not use arrondissement-dummies for the matching because balancing on these dummies would require the exclusion of a vast share of conventional farms. In order to obtain propensity scores, we estimate a logit model for adoption of organic farming. As explanatory variables, we use the same subset of covariates x_i that we use for the matching. We use the estimated propensity scores as an additional variable in the genetic matching as suggested by Diamond and Sekhon (2013).

We use a genetic optimization algorithm to find weights of the covariates (including the propensity scores) for calculating generalized Mahalanobis distances that optimize the balancing between the matched samples of organic and conventional households (see Diamond and Sekhon, 2013, for details). The balancing is assessed based on P-values of two-sided two-sample (unpaired) t-tests for equal mean values in the two matched samples. These P-values are calculated for the same subset of covariates x_i that we use for the matching but not for the propensity score. The P-values are maximized by lexical optimization, i.e., when comparing two sets of P-values, the smallest P-values in each of the two sets are compared; if the smallest P-values in the two sets are equal, the second smallest P-values are compared, etc. In the genetic optimization algorithm, we set the population size to 1,000, and we terminate the search procedure when four generations in a row do not improve the balancing.

In order to avoid the matching with dissimilar "nearest neighbors" and to achieve a reasonable balancing between the matched control and treatment groups, we set "calipers" for the propensity score and most of the covariates. We set the caliper for the propensity score to 0.1 so that the propensity score of a matched "nearest neighbor" is allowed to deviate by up to 10 percentage points. We set the calipers for the household size, the health attitude, and the number of PPE items used to 1.5 so that the values of these three integer variables for a matched "nearest neighbor" are allowed to deviate by up to one unit. We set the calipers for the logarithms of the value of household assets and of the land area cultivated with cotton to 0.5 so that the value of household assets and the land area cultivated with cotton of a matched "nearest neighbor" is allowed to be up to $\exp(-0.5) - 1 = 39\%$ lower and up to $\exp(0.5) - 1 = 65\%$ higher. Finally, in order to achieve balancing regarding the dummy variable for eating during pesticide application, we need to set the caliper of this variable to smaller than one so that exact matching on this variable is imposed.[27]

Given that the per-capita health expenditure in our data set has a very right-skewed distribution, we use IHS-transformed values of this variable as outcome variable in order to avoid unreliable results in the calculation of the average treatment effect due to extreme values. Given that the mean value of the per-capita health expenditure is rather large (see Table 1), we use the approximate formula derived by Bellemare and Wichman (2020) to calculate the semi-elasticity of switching from conventional to organic farming, i.e., $\tilde{\varepsilon}_{(y_i/D_i)} = \exp(ATE) - 1$, where ATE is the average treatment effect obtained from the genetic matching. We apply the Delta method to calculate the approximate standard error of the semi-elasticity of organic farming by:

$$se\left(\tilde{\varepsilon}_{(y_i/D_i)}\right) = \sqrt{\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial (ATE)} \text{VAR}(ATE) \frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial (ATE)}} \tag{G.1}$$

with:

$$\frac{\partial \tilde{\varepsilon}_{(y_i/D_i)}}{\partial (ATE)} = \exp(ATE) \tag{G.2}$$

so that we get:

$$se\left(\tilde{\varepsilon}_{(y_i/D_i)}\right) = \exp(ATE)\, se(ATE), \tag{G.3}$$

where $se(ATE) = \sqrt{\text{VAR}(ATE)}$ is the estimated standard error of the average treatment effect obtained from the genetic matching.

[27] In case of dummy variables, caliper values that are one or larger than one are ineffective, while caliper values that are smaller than one impose exact matching. There is nothing in between these two extremes.

H Additional Tables

Table H.1 presents regression results for different units of measurement of the health expenditure. Tables H.2 and H.3 present the results of balancing tests for the covariates before and after the genetic matching with and without PPE, respectively.

Table H.1: Criteria for selecting the unit of measurement of the per-capita health expenditure

unit of measurement	Semi-elasticity: PPE (Conventional)	Semi-elasticity: PPE (Organic)	Semi-elasticity: Organic	rSquared	pSquared	logLik	logLikAdj	Kolmogorov-Smirnov	Shapiro-Wilk	Shapiro-Fancia	Anderson	Jarque-Bera	Pearson	kurtosis	skewness	Breusch-Pagan	RESET
10^{9} FCFA	-0.08	-0.03	-0.56	0.045	0.003	**10519**	-14432	0.26	0.23	0.22	195	32510585715	1936	772.6	25.1	**26.5**	92.5
10^{8} FCFA	-0.08	-0.03	-0.56	0.045	0.003	7747	-14432	0.26	0.23	0.22	195	32505569493	1936	772.6	25.1	26.5	92.5
10^{7} FCFA	-0.08	-0.03	-0.56	0.046	0.003	4977	-14429	0.26	0.23	0.22	194	32010252947	1934	771.1	25.1	26.5	92.2
10^{6} FCFA	-0.08	-0.01	-0.54	0.051	0.010	2374	-14260	0.25	0.27	0.26	176	10910610128	1689	665.5	22.6	26.7	72.6
10^{5} FCFA	-0.08	0.06	-0.44	0.094	0.059	418	-13467	0.19	0.62	0.61	91	3746716	768	84.4	6.3	32.2	9.7
10^{4} FCFA	-0.08	0.06	-0.36	0.161	0.129	-1165	-12729	0.09	0.93	0.93	20	914	209	5.8	1.2	51.4	**0.9**
10^{3} FCFA	-0.16	0.09	-0.40	0.197	0.166	-1892	-12463	**0.04**	**0.99**	**0.99**	**2**	**3**	**52**	**3.0**	**-0.1**	49.8	7.3
10^{2} FCFA	-0.27	0.09	-0.45	**0.204**	**0.174**	-2289	-12533	0.10	0.94	0.94	22	365	250	3.9	-0.9	108.5	24.8
10^{1} FCFA	-0.39	0.07	-0.49	0.201	0.171	-2619	-12604	0.14	0.88	0.88	46	1628	482	5.1	-1.4	138.2	38.6
FCFA	-0.50	0.06	-0.53	0.197	0.167	-2897	-12624	0.16	0.83	0.83	65	3497	628	5.8	-1.7	150.7	46.6
10^{-1} FCFA	-0.62	0.05	-0.56	0.193	0.163	-3130	-12599	0.18	0.80	0.80	79	5409	726	6.2	-1.8	157.4	51.2
10^{-2} FCFA	-0.73	0.04	-0.59	0.190	0.160	-3329	-12540	0.19	0.78	0.78	87	7047	791	6.5	-1.9	161.5	54.0
10^{-3} FCFA	-0.84	0.02	-0.62	0.187	0.157	-3501	-12455	0.20	0.77	0.77	94	8365	842	6.7	-2.0	164.3	55.8
10^{-4} FCFA	-0.96	0.01	-0.65	0.185	0.155	-3653	-12349	0.20	0.76	0.76	98	9375	882	6.8	-2.0	166.4	57.0
10^{-5} FCFA	-1.07	-0.00	-0.68	0.184	0.153	-3789	-12226	0.21	0.75	0.75	101	10167	918	6.9	-2.0	167.9	57.8
10^{-6} FCFA	-1.18	-0.01	-0.70	0.182	0.152	-3911	-12090	0.21	0.75	0.75	104	10784	938	6.9	-2.1	169.1	58.4
10^{-7} FCFA	-1.30	-0.03	-0.72	0.181	0.150	-4022	-11944	0.21	0.74	0.74	106	11269	959	7.0	-2.1	170.1	58.9
10^{-8} FCFA	-1.41	-0.04	-0.74	0.180	0.149	-4124	-11788	0.22	0.74	0.74	107	11646	961	7.0	-2.1	170.9	59.3
10^{-9} FCFA	-1.52	-0.05	-0.76	0.179	0.148	-4218	**-11624**	0.22	0.74	0.74	108	11951	974	7.0	-2.1	171.6	59.5

Note: column 'unit of measurement' indicates the unit of measurement of the per-capita health expenditure; the three columns that start with 'Semi-elasticity' indicate the three estimated semi-elasticities as described in the note below Table 3; all other column headings indicate criteria for selecting the optimal unit of measurement of IHS-transformed variables as explained in Table 1 of Aïhounton and Henningsen (2021).

Table H.2: Balancing tests with PPE

	Household size	log(Household assets)	log(Land cultivated with cotton)	Training on pesticide application	Eating during pesticide application	Health attitude	PPE
mean organic, unmatched	7.08	13.71	0.11	0.34	0.09	1.35	1.67
mean conventional, unmatched	7.41	14.03	1.09	0.12	0.15	3.33	2.37
P-value, unmatched	0.24	0.00	0.00	0.00	0.01	0.00	0.00
mean organic, matched	6.58	13.60	0.67	0.13	0.01	1.56	1.88
mean conventional, matched	6.51	13.62	0.70	0.15	0.01	1.61	1.93
P-value, matched	0.74	0.78	0.51	0.41	1.00	0.53	0.54

Note: The P-values are obtained by two-sided two-sample (unpaired) t-tests for equal mean values.

Table H.3: Balancing tests without PPE

	Household size	log(Household assets)	log(Land cultivated with cotton)	Training on pesticide application	Eating during pesticide application	Health attitude
mean organic, unmatched	7.08	13.71	0.11	0.34	0.09	1.35
mean conventional, unmatched	7.41	14.03	1.09	0.12	0.15	3.33
P-value, unmatched	0.24	0.00	0.00	0.00	0.01	0.00
mean organic, matched	6.55	13.70	0.67	0.13	0.01	1.80
mean conventional, matched	6.52	13.70	0.69	0.15	0.01	1.85
P-value, matched	0.86	0.93	0.61	0.54	1.00	0.61

Note: The P-values are obtained by two-sided two-sample (unpaired) t-tests for equal mean values.

I Additional Figure

Figure I.1 illustrates the relationship between the number of PPE items used by a farmer and the social norm of PPE use by peers in the village.

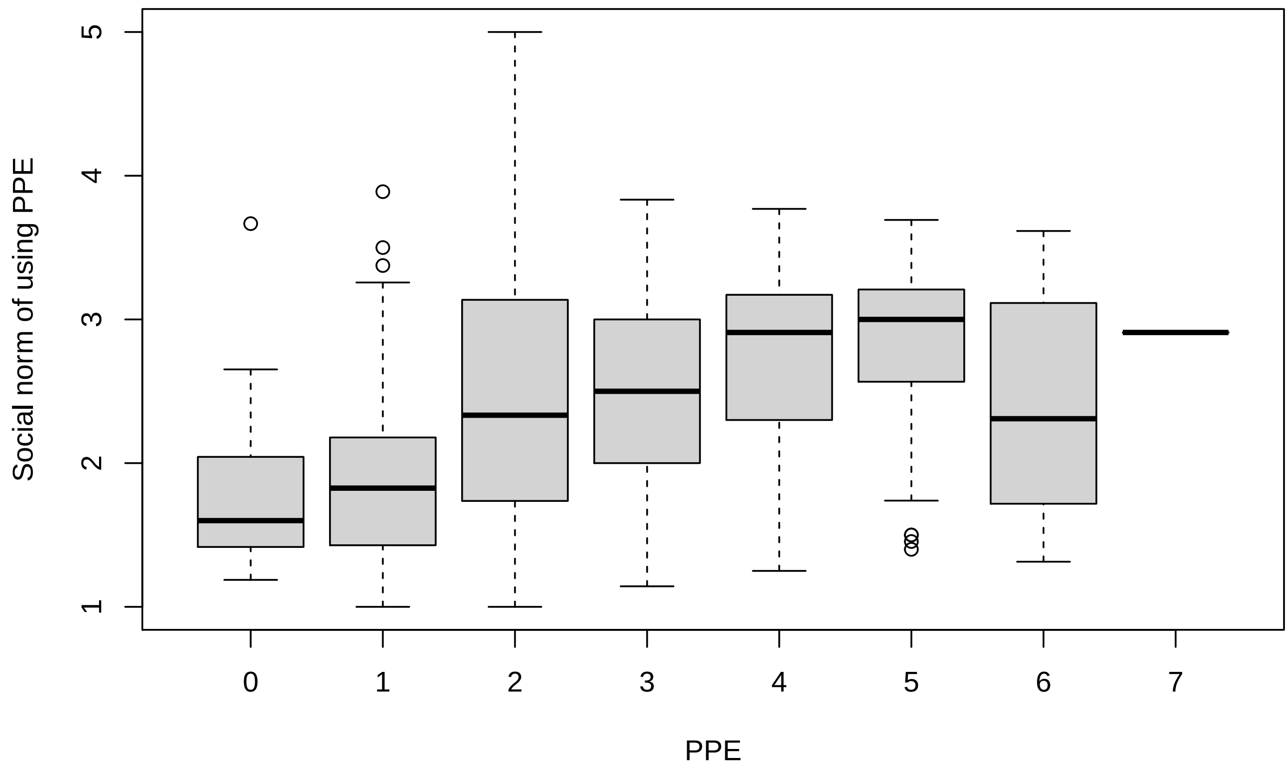

Figure I.1: Relationship between PPE and the social norm of using PPE

J R packages

We used the following add-on packages to the statistical software "R" (R Core Team, 2021) for conducting the empirical analyses that are presented in our study:

- "AER" (Kleiber and Zeileis, 2008)
- "ggplot2" (Wickham, 2016)
- "censReg" (Henningsen, 2020)
- "Matching" (Sekhon, 2011)
- "rgenoud" (Mebane, Jr. and Sekhon, 2011)
- "sandwich" (Zeileis, 2004, 2006; Berger et al., 2017)
- "sjPlot" (Lüdecke, 2021)
- "sjmisc" (Lüdecke, 2018)
- "sm" (Bowman and Azzalini, 2018)
- "stargazer" (Hlavac, 2018)
- "xtable" (Dahl et al., 2019).