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Does it matter who advises farmers? Pest management choices with public and private extension

David Wuepper *, Nikolaus Roleff, Robert Finger

Agricultural Economics and Policy Group, ETH Zurich, Sonneggstrasse 33, 8092 Zurich, Switzerland

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ABSTRACT

Does it matter whether farmers receive advice on pest management strategies from public or from private (pesticide company affiliated) extension services? We use survey data from 733 Swiss fruit growers who are currently contending with an infestation by an invasive pest, the fruit fly *Drosophila Suzukii*. We find that farmers who are advised by public extension services are more likely (+9–10%) to use preventive measures (e.g. nets) while farmers who are advised by private extension services are more likely (+8–9%) to use synthetic insecticides. These results are robust to the inclusion of various covariates, ways to cluster standard errors, and inverse probability weighting. We also show that our results are unlikely to be driven by omitted variable bias. Our findings have implications for the current debates on both the ongoing privatization of agricultural extension and concerns regarding negative environmental and health externalities of pesticide use.

1. Introduction

The realization of more sustainable agricultural systems depends on farmers' production and technology choices which, in turn, are based on information and social learning. In the agricultural economics literature, a lot of empirical research has focused on what farmers learn from their peers, their own experience, and from extension services (Genius et al., 2013, Krishnan and Patnam, 2013, Wuepper et al., 2017). It is important, both for the academic literature and policy making, to understand how different information sources influence farmers' behavior, as this affects the optimal public spending on extension services as a range of economic and environmental outcomes. It has been found that extension services are especially important in relation to new technologies (Krishnan and Patnam, 2013), in particular for those which are more complex and demanding (Wuepper, et al., 2017), and they are complementary with learning from other farmers (Genius et al., 2013). Moreover, extension often plays a key role in farmers' pest management choices (Feder et al., 2003, Lichtenberg and Zimmerman, 1999, Möhring et al., 2020c) which is highly relevant for current policy making (Antle, 2015, Finger, 2018, Lefebvre et al., 2015, Möhring et al., 2020a). Important global trends indicate that pest pressure is increasing, e.g. due to climate change (Deutsch et al., 2018) and extension services are being privatized (Anderson and Feder, 2007, Feder et al., 2011, Labarthe and Laurent, 2013, Schnyder et al., 2019, Wolf and Zilberman, 2012). At the same time, there is increasing public concern regarding environmental impacts and human health effects of pesticide use (Schaub et al., 2020). In addition, the issue of pesticide-resistance is becoming ever more important (Brown, 2018). In this situation, where farmers' pest management choices have a direct impact not only on their own welfare, but on that of their neighbors and the public at large, extension services are crucial to steer pest management strategies towards overall welfare maximization (Fan et al., 2020, Pannell, 2008, Schnyder et al., 2019).

We are the first to analyze empirically whether farmers' use of pesticides and prevention measures differ systematically depending on who advises them. The main hypothesis is that farmers who are advised by public extension services are more likely to use non-chemical preventive measures, and farmers who are advised by private extension services are more likely to use synthetic pesticides. To test this hypothesis, we use survey data from 733 Swiss fruit growers who are currently contending with an infestation by a new invasive pest, the fruit fly *Drosophila Suzukii*.

It has previously been found that extension services affiliated with companies selling pesticides increase farmers' use of pesticides (Wiebers et al., 2002). Analysis of farmers' action against *Drosophila Suzukii*, Fan et al. (2020) also reveals evidence of misalignments between public and private incentives when it comes to the use of pesticides. Farmers who fully internalize the external costs of their pesticide applications (e.g. future pesticide-resistance, environmental damage, human health

* Corresponding author.
E-mail address: dwuepper@ethz.ch (D. Wuepper).

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impacts) use more monitoring and less pesticides, while other farmers overuse pesticides instead of more monitoring.

Our assumption is that public extension services tend to internalize the public good aspect of reduced pesticide applications more strongly than private extension services, which are more concerned about company profits and farmers' private welfare (Schnyder et al., 2019, Wiebers, et al., 2002, Zhang et al., 2007). When addressing the use of pesticides, public extension agents are motivated to draw attention to the adverse effects on the environment, possible health risks for consumers, farmers and bystanders and the build-up of pesticide-resistance (Grovermann et al., 2013, Sexton et al., 2007, Tilman et al., 2011) and to recommend strategies that can reduce pesticide applications, whereas private extension services have no incentive to do so.

There is a wealth of literature on pesticide use and its determinants (Fan et al., 2020, Liu and Huang, 2013, Möhring et al., 2020b, Möhring et al., 2020c, Serra et al., 2005, Sunding and Zivin, 2000). Earlier literature has also addressed pest prevention measures, their adoption and interdependencies with pesticide use (Brown, 2018, Kan et al., 2013, Olson and Roy, 2005). However, the link between extension source, adoption of preventive measures and pesticide applications has not been empirically established in the literature so far.

We contribute to filling this gap and test the hypothesis that farmers who are advised by public extension services are more likely to use non-chemical preventive measures, and those who are advised by private extension services are more likely to use synthetic insecticides. The farmers in our sample currently face the challenge of having to contend with the fruit fly *Drosophila Suzukii,* a new invasive pest with high economic damage potential (Asplen et al., 2015). Fruit infested with *D. Suzukii* is unmarketable (Farnsworth et al., 2017) and often entire deliveries are rejected, making *D. Suzukii* a particularly costly pest. In addition, production costs increase with the share of infested fruit as labor costs for inspection and sorting rise while the percentage of sellable fruit sinks (Mazzi et al., 2017). Different pest management strategies have been developed in response to the outbreak of *D. Suzukii.* They involve both preventive, non-chemical measures as well as synthetic contact insecticides (Knapp et al., 2019b). However, it is costly (in time and money) and risky for individual farmers to experiment with different prevention and control strategies against new pests and so producers have an increasing need for information (Park and Lohr, 2005).

Consistent with our hypothesis, we do indeed find that farmers who receive their advice from a public extension services are more likely to use preventive measures (e.g. nets) while those advised by private extension services are more likely to use synthetic insecticides.

These results are robust to controlling for other sources of information such as peers and own research, farmers' age, gender, earnings, risk preferences, farm size and area of leased land, as well as the actual infestation level, as well as fixed effects for main production, sampling year, and Canton, and using standard errors that account for intra-Canton dependence of observations and heteroscedasticity. They are also robust to distinctly weighting observations according to their probability of receiving public or private extension advice (i.e. inverse probability weighting, see e.g. Hernan and Robins, 2019) and to allowing for combinations of advice and pest management choices, as well as the number of different extension sources. Finally, we use techniques developed by Imbens (2003), Altonji et al. (2005), and Oster (2019) to use observed selection on observables to understand potential severity of selection on unobservables (i.e. omitted variable bias). These suggest that our results are unlikely driven by selection on unobservables, as they would need to be multiple times stronger than selection on observables.

In the next section (2), we describe the background of our analysis and our data. We then explain our empirical framework (3), present our main results (4), and further analyses (5). Finally, we conclude (6).

2. Background and data

In Switzerland, *D. Suzukii* was first detected in 2011 (Mazzi et al., 2017). This pest can lead to substantial damage in various horticultural products and necessitates the implementation of costly management measures. A recent survey shows that while the actual yield losses caused by *D. Suzukii* in Swiss fruit production are relatively small, the majority of farmers report significant cost increases to control or prevent infestation. A wide range of measures is available to manage *D. Suzukii,* but none of them is entirely effective on its own and not all are always cost-efficient. Moreover, many farmers are still uncertain about the efficacy of these measures as *D. Suzukii* is a relatively new pest and little experience has been amassed so far. Frequently used pest management strategies include: (i) preventive, non-chemical measures (such as netting, early/short interval harvests, infestation control, and various hygiene measures), (ii) the use of synthetic insecticides[1]. Preventive measures, ceteris paribus, reduce pest pressure and thus contribute to reduced insecticide use. Moreover, some producers use the clay-mineral Kaolin (e.g. Surround). Kaolin has a repellent effect and dissuades oviposition, but poses no significant hazards to human health[2]. Table 1 gives an overview on the used strategies in order to cope with *D. Suzukii*.

Data was collected by means of an online survey which was distributed to producers of cherries, berries, grapes, and plums all over Switzerland, between 2016 and 2018 in the official language of each region (German, French, and Italian). To encourage participation, a lottery was organized, in which participants could win one of four 50 CHF vouchers. In addition, as a further incentive to contribute, participants could opt to receive individualized information on the results and feedback by mail (see Knapp et al., 2019 for further details). We only consider non-organic farms (89% of total sample) because the use of synthetic pesticides is banned on organic farms. Our final dataset consists of complete data for 733 farmers from all over Switzerland and especially the major fruit and grape production regions (Fig. 1). The data is publicly accessible (Knapp et al., 2019a). The survey included sections on varieties of fruits, cultivated areas, perceived infestation levels, measures taken, and farm and farmer characteristics.

Fruit growers in Switzerland have access to multiple sources of information on pest management in general and *D. Suzukii* in particular. These information sources are grouped in (i) public extension services, (ii) private extension services, (iii) other farmers and (iv) own information search. Public extension services are financed by the government with tax money (see Buess et al., 2011), for an overview of the Swiss public extension system) and also include extension services at cantonal levels[3]. Moreover, Agroscope, the Swiss Center of Excellence for

Table 1
Overview of strategies adopted (in %).

Strategy	Berries	Cherries	Plums	Grapes
Prevention	89	87	86	83
- Hygiene measures	73	66	50	52
- Infestation CONTROL	65	55	47	39
- Early/short interval harvest	69	26	25	14
- Netting	35	63	9	17
Synthetic pesticides	33	70	49	12
Kaolin	0	2	3	53

Note: The table shows shares of the sample using a specific strategy. More than one strategy could be indicated.

[1] These comprise Thiacloprid (e.g. Alanto), Spinosad (e.g. Audienz), Acetamiprid (e.g. Gazelle SG), Pyrethrine (e.g. Parexan N)).

[2] Kaolin is mainly relevant in grape production. Otherwise the use of Kaolin is restricted to fruit used for distilling which only plays a minor role in our sample.

[3] These cantonal activities are further supported by the agricultural extension center of the cantonal extension services, Agridea.

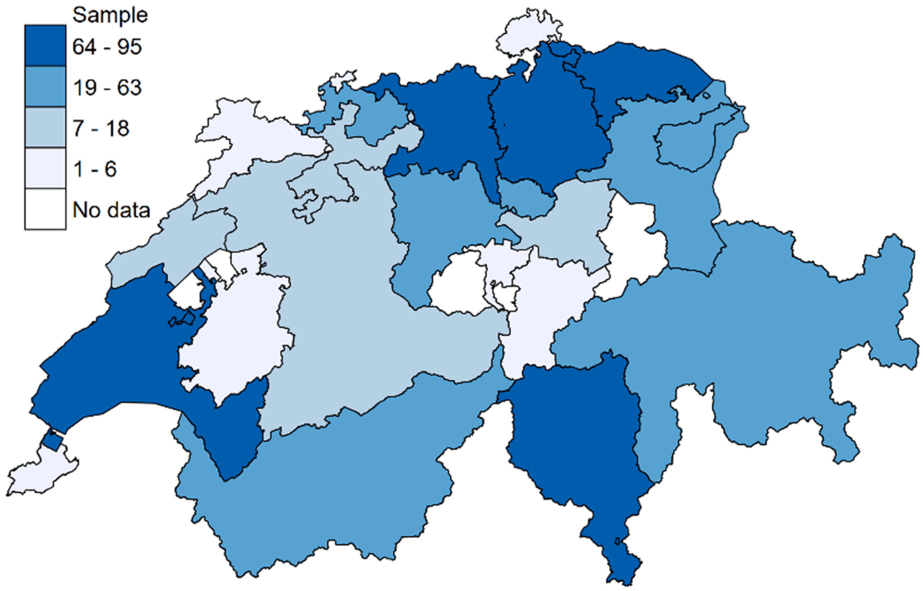

Fig. 1. Participation in the survey from 2016 to 2018. Note: the figure shows the absolute number of participants from different Swiss cantons.

Agricultural Research, offers information events and material for farmers. In 2015, Agroscope also created a 'Task Force *D. Suzukii*' that provides information (e.g. publications, events) and extension services targeted at *D. Suzukii* (e.g. Mazzi et al., 2017). There are also various private extension services available to farmers in Switzerland. More specifically, companies specializing in plant protection and agricultural input suppliers offer farmers a wide range of extension focusing on plant protection and more. All public and private extension and information services are available across the entire country. Moreover, farmers can obtain information and advice from other farmers, either bilaterally or via specific associations. Information provided by the Swiss Fruit Producer Association is particularly relevant in this context. Finally, farmers also search for information themselves, e.g. from specialist articles, journals, and the web.

Table 2 gives an overview of who advised the farmers on how to deal with *D. Suzukii.* We obtained this information by asking farmers where they acquired their expertise about *D. Suzukii* and how to react to it. Multiple sources of information could be indicated. In total, 19% received both public and private extension on *D. Suzukii,* 52% received public and 34% received private extension. 33% received extension from neither public nor private services, but preferred to get their information on *D. Suzukii* through their own research and by asking other farmers. Table 3 summarizes all our main variables.

Table 2
Overview of information sources.

Category	Source	Berries %	Cherries %	Grapes %	Plums %
Public	*Total Public*	63	66	41	57
	Agroscope	57	55	74	61
	Plant protection news	–	–	15	–
	Info days at Agroscope for producers	24	–	–	–
	Breitenhof conference	–	16	–	15
	Newsletter TaskForce/Swiss Berry Note	18	–	8	–
	Cantonal specialist units	80	82	76	77
	Cantonal consulting service and meetings	59	49	15	53
Private	*Total Private*	36	48	24	39
	Plant protection firms	30	20	18	36
	Input suppliers	12	41	9	9
Other Farmers	*Total Other Farmers*	69	12	35	34
	Information of Swiss Fruit Associations	31	–	–	–
	Other producers	61	12	35	34
Own	*Total Own*	55	74	57	67
	Internet	25	47	27	22
	Specialist articles/ journals	45	56	42	56
	Others (e.g. special symposiums)	6	5	7	3

3. Empirical framework

We are interested in the relationship between the kind of extension service (public or private) on the one hand, and the choice of pest management strategy (non-chemical prevention and the use of insecticides) on the other. We estimate variations of:

$$P_{i,n}^{choice} = \alpha_0 + \beta_1 Extension_i + \beta_2 X_i + \beta_3 \tau_i + \varepsilon_i \quad (1)$$

were $P_{i,n}^{choice}$ is the probability that farmer n chooses strategy i, which is insecticides (yes or no) and preventive strategies (yes or no), $Extension_i$ is who advised the farmer, that is private extension (yes or no) and public extension (yes or no), X_i is a vector of control variables that we vary to investigate the reliability of our estimates in various ways, as explained further below, τ_i is a vector of fixed effects for the four fruits, the cantons, and the years of the survey, and ε_i is a residual term. Regarding $P_{i,n}^{choice}$, we focus on non-chemical preventive strategies and the use of synthetic insecticides[4].

We estimate whether there is significant relationship between $P_{i,n}^{choice}$ and $Extension_i$, as expressed by β_1. We use a linear probability model

[4] We also explored the relationship between extension services and the use of Kaolin but did not find any (results are available upon request)

Table 3
Description of variables.

Variable	Description	Mean	Std Dev.
Public extension	Dummy variable (1/0) for use of public extension service	0.515	0.500
Private extension	Dummy variable (1/0) for use of private extension service	0.335	0.472
All extension	Dummy variable (1/0) for use of both public and private extension	0.1909	0.393
No extension	Dummy variable (1/0) for use of neither public nor private extension services	0.339	0.473
Number private	Count variable for number of different private extension services (i.e. plant protection firms and input suppliers)	0.410	0.626
Number public	Count variable for number of different public extension services (see Table 1)	0.652	0.728
Own learning	Dummy variable (1/0) if the farmer did his own research (e.g. in the internet)	0.639	0.480
Social learning	Dummy variable (1/0) if the farmer learned strategy from other farmers (e.g. imitation)	0.341	0.474
Preventive measures	Dummy variable (1/0) if the farmer used at least one preventive measure	0.848	0.358
Insecticides	Dummy variable (1/0) if the farmer used at least one insecticide	0.248	0.432
Both strategies	Dummy variable (1/0) if farmer used both preventive measures and insecticides	0.229	0.420
Neither	Dummy variable (1/0) if farmer used neither strategy	0.132	0.339
Year of birth	Year of birth of farmer	1966	11.484
Farm Earnings	Dummy variable for share of farm earnings in total household income (1 = <25%; 2 = 26–50%; 3 = 51–75%; 4 = > 76%)	2.993	1.2451
Gender	Dummy variable for farmer's gender, 0 = male, 1 = female	0.054	0.227
Risk preferences	Average stated willingness to take risks in the domains production, market and prices, external financing, and agriculture in general on an 11 point likert scale (from 1 = not willing to take a risk at all to 11 = very willing to take a risk).	4.233	2.082
Farm size	Total farm size in hectares	13.855	19.598
Leased Land	Dummy variable for share of leased land (1 = <25%; 2 = 26–50%; 3 = 51–75%; 4 = >76%)	1.969	1.092
Infestation level	Dummy variable for infestation levels. The average infestation was collected on a scale from 0 to 7 for each fruit (0 = 0%; 1 = 1–5%; 2 = 6–10%; 3 = 11–15%; 4 = 16–20%; 5 = 21–25%; 6 = 26–30%; 7 = >30%). Here, the analysis is based on the average infestation of all infested varieties on a farm, weighted by acreage.	0.469	0.803
Fruit	Plums, grapes, berries, cherries		
Canton	The cantons of Switzerland		
Year	2016, 2017, 2018		

Notes: Statistics based on sample of 733 farmers. See Appendix Figs. S1 and S2 for maps of the spatial distribution of information sources and pest management strategy.

based on OLS but Tables S6 and S7 in the Appendix show that logit and probit models also give the same results. See also Angrist and Pischke (2008) for explanation.

A technical complication that arises is that with a binary dependent variable, clustered standard errors are not heteroscedasticity robust. At the same time, standard heteroscedasticity robust standard errors do not correct for the fact that observations are not independent from each other, but within the Cantons, there are observed and unobserved commonalities. Here, this is especially important as many extension services are organized at the cantonal level. For this reason, we use both clustered and heteroscedasticity robust standard errors, to assess whether either correction is strictly necessary.

Obviously, omitted variable bias is another matter of concern. For example, private extension services could concentrate mainly on larger, more professional farms, and public extension services could then step in, focusing on those farms which have been disregarded. We approach this in several ways.

Firstly, our vector of control variables X_i covers a diverse set of farm and farmer characteristics, including other information sources (learning from own research and other farmers), the age and gender of the farmers, farm size, amount of leased land, their risk preferences, and level of *Drosophila Suzukii* infestation. These covariates were chosen because each could potentially be correlated with the farmers' choice of extension source and pest management strategy. For example, farmers with higher infestation levels might be more likely to get special attention from public extension services and they are probably more inclined to use a pest management strategy. Alternatively, instead of, or in addition to, getting special attention from public extension, farmers with more infested fields might prefer to contact private extension services themselves, asking for other strategies. Either way, classic omitted variable bias could arise if differences in infestation levels are not controlled. As a second example, farmers' risk preferences could depend on whose recommendations they seek most frequently and which strategies are more likely to be favored. The inclusion and exclusion of these covariates indicates the overall magnitude of selection and how sensitive our estimates are to the choice of what to control for. We describe more formal versions of such tests below.

We also estimate inverse probability weighted regressions, which are based on two stages. In the first stage, the probability of receiving public or private extension is estimated (based on all observed farm and farmer characteristics). In the second stage, farmers with a higher likelihood of receiving advice from a certain source receive a lower weight, proportional to the estimated degree of selection (Hernan and Robins, 2019). A crucial requirement for inverse probability weighting is that for each propensity to receive public or private advice, we have farmers in our sample who then received that advice and others who did not ("overlap"). In the Appendix in Fig. S3 we show that this is fulfilled here.

We then leverage different approaches to assess (**a**) the probability and possible magnitude of selection biases and (**b**) potential implications.

The degree to which this selection affects our estimates is already explored in our main analysis by simply comparing our estimates from specifications with different covariates and fixed effects. The larger selection on observables becomes, the greater our concern about selection in general, including on unobservables (Rosenbaum and Rubin, 1983). This reasoning can also be applied more rigorously methodologically. The first approach was proposed by Altonji et al. (2005) and then refined and improved by Oster (2019). The second approach was developed by Imbens (2003). The first approach produces two valuable indicators: First, in our baseline, specifications are based on the assumption of no selection on unobservables (possibly conditional on including our covariates and fixed effects). We choose to relax this assumption and assume a certain degree of selection on unobservables and simulate the changes in our estimated relationships. Secondly, and even more informative, we can also estimate how much selection on unobservables would be required to cancel out the statistical significance of the relationships previously estimated. We commence by estimating a specification which includes all control variables and save the estimated coefficient which we name $\widehat{\beta}_F$. Then, we estimate a second specification without controls and save the estimated coefficient which we name $\widehat{\beta}_R$. Omitting technicalities, such as the weighting of covariates by explanatory power and similar, the ratio of $\widehat{\beta}_{1,F}$ to the difference $\left(\widehat{\beta}_{1,R} - \widehat{\beta}_{1,F}\right)$ gives us an indicator for how much stronger selection on unobservables (δ^U) relative to selection on observables (δ^O) would need to be to explain away an estimated relationship ($\delta^{\beta=0}$):

$$\delta^{\beta=0} = \widehat{\beta}_{1,F} \Big/ \left(\widehat{\beta}_{1,R} - \widehat{\beta}_{1,F}\right) \tag{2}$$

See Oster (2019) for a more extensive discussion of this approach. The other technique used here is the generalized sensitivity analysis proposed by Imbens (2003). This allows a visual comparison of selection on observables and selection on simulated pseudo-unobservables. In this approach, the comparison is based on partial R^2s per individual control variable. The idea is that selection is implicated if a control variable is highly predictive for indicating both which farmers receive a certain type of extension service and the strategy they choose. By understanding the degree of selection on observables, we can assess the plausibility of the existence of unobserved confounders having a comparable – or larger - selection effect. For example, if we would estimate that the exclusion of farm size would result in a 10% overestimation of the relationship between private extension and insecticide use, and we would be interested in unobserved confounders that could reduce our main estimate by 50%, we would need to think about the plausibility that unobserved variables exist that could cause a selection effect that is five times stronger than what we found for farm size.

Finally, we extend our main analysis in two ways. First, we estimate whether it matters how many public and private extension sources advice a farmer (see Table 2 for an overview).

$$P_{i,n}^{choice} = \alpha_0 + \beta_1 Number\_Private_i + \beta_2 Number\_Public_i + \beta_3 X_i + \beta_4 \tau_i + \varepsilon_i \tag{3}$$

Secondly, we estimate not only the association between private and public extension and preventive measures and pesticides, but also the association between a combination of both public and private extension and a combination of both prevention and pesticides, as well as no extension service and no pest management:

$$P_{i,n}^{choice} = \alpha_0 + \beta_1 Extension_i + \beta_2 X_i + \beta_3 \tau_i + \varepsilon_i \tag{4}$$

were $P_{i,n}^{choice}$ is the probability that farmer n chooses strategy i, which is here (a) only insecticides, (b) only preventive measures, (c) both, or (d) none, $Extension_i$ is who advised the farmer, which is here (a) only private, (b) only public, (c) both, or (d) neither, X_i is the same vector of control variables as before, τ_i is the same vector of fixed effects as before, and ε_i is a residual term.

The statistical significance of our last estimates is computed by correcting the p-values for the rate of false discoveries (which is higher here because we test several hypotheses at once). We use the approach of Anderson (2008) for this correction. We show both standard and corrected p-values in Table S9 in the Appendix for comparison.

4. Results

Our main result is presented in Table 4. We estimate three specifications for each strategy choice: The first only include fixed effects for survey and year but no other covariates and no fixed effects for cantons. The second specifications include a vector of controls (see Table S5 in the Appendix for all coefficients) but still no fixed effects for cantons. The third specifications also include cantonal fixed effects.

We estimate that public extension is empirically associated with a 9–10 percentage points increase in the probability that a farmer uses preventive measures (e.g. nets or hygiene measures). We do not find any relationship between private extension and the use of preventive measures. The pattern is reversed for the probability that a farmer uses insecticides. We find no relationship between public extension and the use of insecticides, but we find that farmers who receive their advice from private extension are 8 – 9 percentage points more likely to use synthetic insecticides.

Next, we use inverse probability weighting to test the robustness of our estimates in relation to potential selection (Hernan and Robins, 2019). The idea is to estimate the degree of selection into private and public extension first and then to attempt to correct for it statistically by weighting the estimates according to the inverse of the estimated selection. Table 5 presents the results, which are consistent with our previous estimates. The adjustment for observable selection slightly reduces our baseline estimates for the relationship between public extension and the use of preventive measures and the relationship between private extension and the use of insecticides from 9 to 10% to 9% and from 8 to 9% to 7%, respectively.

Instead of attempting to correct statistically for potential selection, we next seek to quantify the degree to which selection could affect our estimates if we did not correct for it. Table 6 presents a formal analysis of **(a)** how much stronger selection on unobservables relative to selection on observables (delta), would be necessary to fully explain away our

Table 5
Results Inverse Probability Weighting.

	(1) Prevention	(2) Prevention	(3) Insecticides	(4) Insecticides
Public Extension	0.0942***		0.0221	
	(0.0277)		(0.0266)	
	(0.0164)		(0.0271)	
Private Extension		0.0228		0.0682**
		(0.0303)		(0.0269)
		(0.0322)		(0.0265)
N	733	733	733	733

Notes: Significance levels are 10% (*), 5% (**), and 1% (***). Table presents inverse probability weighting estimates and clustered (first line) and heteroscedasticity robust standard errors (second line) in brackets. Covariates include other information sources (learning from own research and other farmers), the age and gender of the farmers, farm size, amount of leased land, risk preferences, and level of *Drosophila Suzukii* infestation.

Table 4
The association of extension source and pest management strategy.

	(1) Prevention	(2)	(3)	(4) Insecticides	(5)	(6)
Public Extension	0.105***	0.0930***	0.0897***	0.0299	0.0219	0.0299
	(0.0145)	(0.0169)	(0.0193)	(0.0278)	(0.0266)	(0.0313)
	(0.0275)	(0.0283)	(0.0290)	(0.0268)	(0.0274)	(0.0279)
Private Extension	0.0497	0.0274	0.0285	0.0934***	0.0864**	0.0793**
	(0.0306)	(0.0276)	(0.0286)	(0.0300)	(0.0325)	(0.0342)
	(0.0265)	(0.0273)	(0.0285)	(0.0293)	(0.0304)	(0.0307)
Covariates	N	Y	Y	N	Y	Y
Survey and Year FE	Y	Y	Y	Y	Y	Y
Canton FE	N	N	Y	N	N	Y
R^2	0.044	0.066	0.109	0.387	0.396	0.428
N	733	733	733	733	733	733

Notes: The table presents the estimates from a linear probability model (OLS) and below two kinds of standard errors in brackets. The first row shows standard errors clustered by Canton, the second row shows heteroscedasticity robust standard errors. Statistical Significance Levels:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Covariates include other information sources (learning from own research and other farmers), the age and gender of the farmers, farm size, amount of leased land, risk preferences, and level of infestation. See Table S5 in the Appendix for all coefficient estimates and Tables S6 and S7 for alternative logit and probit estimates.

Table 6
Quantifying the potential for omitted variable bias.

	Public extension		Private extension	
	(1)	(2)	(3)	(4)
Beta	0	0.07	0	0.05
Delta	2.65	1	2.09	1
R^2 max	0.09	0.09	0.51	0.51
N	733	733	733	733

Notes: In specifications (1) and (3), we set the estimated coefficient to zero and estimate the required degree of omitted variable bias. In specifications (2) and (4), we set omitted variable bias to equal selection on included control variables and estimate the resulting coefficient. See Oster (2019).

main initial estimates (beta = 0), and **(b)** how our main estimates would change (beta) if selection on unobservables was as strong as selection on observables (delta = 1) (Oster, 2019). For the relationship between public extension and the use of preventive measures, we estimate that omitted variable bias would need to be almost three times stronger than observed selection to explain away our initial estimate. With equal selection, our baseline estimate would shrink from 9 − 10% to 7%. Regarding the relationship between private extension and pesticide use, we estimate that omitted variable bias would need to be twice as strong as observed selection explain away our initial estimate. With equal selection, our baseline estimates would shrink from 8 − 9% to 5%.

Fig. 2 shows the result of Imbens (2003) generalized sensitivity analysis. Part (a) shows the estimated relationship between public extension and the use of preventive measures and part (b) illustrates the estimated relationship between private extension and the use of insecticides. The plots can be interpreted as follows: the bottom left corner shows selection on each covariate indicating how much each covariate explains both "treatment" (extension source) and "outcome" (pest management choice). In the case of the association between public extension and the use of preventive measures, the largest selection effect is estimated for farmers' own learning efforts ("own"). For the association between private extension and the use of insecticides, the largest selection effect is estimated for farm income ("earnings_farming"). This is important information because we are comparing potentially unobserved confounders to these estimated selection effects based on observables. There is a line of simulated pseudo-unobservables in the middle of the plots that would halve the strength of the estimated relationship between the extension type and strategy choice (the "generalized sensitivity analysis bounds"). This allows us to compare the strength of selection on observables with the simulated magnitude of selection on unobservables that would halve the strength of our estimated association between extension source and pest management strategy. It can be observed that all of our control variables are far below the simulated "gsa bounds". This means that omitted variable bias would need to be many times stronger than observed selection to even just halve the strength of our estimated relationships, and twice that to explain it away completely.

5. Further analyses

In this section, we extent our main analysis in two directions. First, we estimate whether additional number of public extension sources is likely to be associated with a higher level of prevention and whether more private extension is apt to generate a higher level insecticide use. Table 7 shows that on average, each additional public extension source leads to an 6 percentage points increase in the probability that preventive measures will be adopted. The probability that insecticides will be used increases by 5 percentage points with each additional private extension source (this, however, is only statistically significant at the 10% level).

Secondly, we consider the various combinations of extension services and strategies that are actually possible. So far, we simplified our analysis by only comparing public and private extension services and estimating their association with ex-ante pest prevention and ex-post pest treatment. However, farmers can seek advice from both public and private extension services and they can adopt both preventive measures and pesticides.

Table 7
Number of extension sources.

	(1) Prevention	(2) Insecticides
Number public extension sources	0.0582^{***}	0.0183
	(0.0112)	(0.0188)
	(0.0175)	(0.0192)
Number private extension sources	0.0138	0.0461^{*}
	(0.0220)	(0.0238)
	(0.0204)	(0.0227)
Covariates	Y	Y
Survey and year fixed effects	Y	Y
R^2	0.06	0.39
N	733	733

Notes: The table presents the estimates from a linear probability model (OLS) and below two kinds of standard errors in brackets. The first row shows standard errors clustered by Canton, the second row shows heteroscedasticity robust standard errors. Statistical Significance Levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Covariates include other information sources (learning from own research and other farmers), the age and gender of the farmers, farm size, amount of leased land, risk preferences, and level of *Drosophila Suzukii* infestation. See Table S7 in the Appendix for all coefficient estimates.

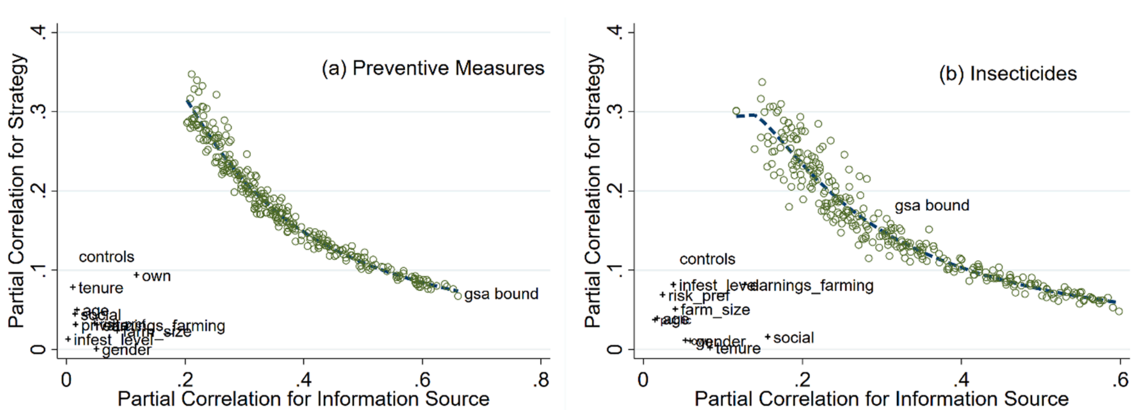

Fig. 2. Generalized sensitivity analysis. Notes: if there were control variables above the lines of simulated pseudo-unobservables, their exclusion would halve the magnitude of the estimated relationships and the plausibility of unobserved confounding variables with a similar or greater effect would demand careful consideration. Here, however, selection on observables is rather weak, so omitted variable bias would need to be implausibly large to fundamentally change our estimates.

Table 8 shows our estimates for all possible combinations of strategies and extension services. The p-values are corrected to account for the fact that we are testing several hypotheses at once (Anderson, 2008). We estimate, as before, that private extension is associated with the use of insecticides while public extension is associated with prevention. However, in addition, we see that private extension is also associated with the use of insecticides *and* prevention in combination. This suggests that private extension is not so much directed at replacing prevention by the use of pesticides but, in general, rather with an increased use of insecticides either alone or in addition to preventive strategies (this, however, is only statistically significant at the 10% level). Finally, we estimate that public extension is negatively associated with no active pest management strategy at all (i.e. neither prevention nor insecticide treatment).

6. Conclusion

We estimate various specifications and use different econometric techniques, which all point in the same direction. This is consistent with our initial hypothesis: There is a systematic difference in pest management strategies adopted by those farmers who are advised by public services and those who are advised by private companies. Using the example of farmers' strategies to control the new, invasive pest *Drosophila Suzukii* in Swiss fruit production, we estimate that preventive measures are more likely being adopted by publicly advised farmers while privately advised farmers are more likely to use synthetic insecticides. When examining combinations, we find that, compared to no extension service, guidance exclusively from a public extension service is associated with a decrease in the likelihood that no pest management strategy is adopted at all, and an increase in the probability that prevention alone is used.

Advice obtained exclusively from private extension services is associated with an increase in both the probability that only insecticides are used, and that insecticides are used together with preventive measures. We detect no additional differences for the combination of public and private extension services. Finally, we find that on average, there is a greater likelihood that farmers who are advised by more (different) public extension sources will adopt preventive measures compared those who are advised by fewer public extension sources. Similarly, farmers who are advised by more (different) private extension sources are more likely to use synthetic insecticides than farmers who consult fewer private extension sources.

Table 8
Combinations.

	(1) Only prevention	(2) Only insecticides	(3) Both	(4) Neither
Public extension	0.113***	0.0222	0.0241	−0.111***
	(0.0202)	(0.0297)	(0.0312)	(0.0242)
	(0.0350)	(0.0309)	(0.0294)	(0.0332)
Private extension	0.0604	0.0869*	0.0778*	−0.0695
	(0.0521)	(0.0442)	(0.0447)	(0.0429)
	(0.0451)	(0.0393)	(0.0382)	(0.0426)
Both services	−0.0611	−0.000827	0.0197	0.0816
	(0.0727)	(0.0580)	(0.0609)	(0.0596)
	(0.0528)	(0.0558)	(0.0557)	(0.0492)
Covariates	Y	Y	Y	Y
Survey and year FE	Y	Y	Y	Y
R^2	0.07	0.40	0.38	0.07
N	733	733	733	733

Notes: The table presents the estimates from a linear probability model (OLS) and below two kinds of standard errors in brackets. The first row shows standard errors clustered by Canton, the second row shows heteroscedasticity robust standard errors. Statistical Significance Levels:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Covariates include other information sources (learning from own research and other farmers), the age and gender of the farmers, farm size, amount of leased land, risk preferences, and level of *Drosophila Suzukii* infestation. Standard errors in parentheses corrected for multiple hypothesis testing (Anderson, 2008). See Table S9 in the Appendix for all coefficient estimates.

A limitation of our study is the fact that the distribution of extension services is not random. Both farmers and extension agents can decide freely with whom they want to interact or not. We have used several approaches to assess the implications. Our results are remarkably robust to the variation of covariates, inclusion of fixed effects, and inverse probability weighting, and we estimate that selection on observables would need to be a few times stronger than selection on unobservables to change our main results. This suggests that there is not actually much selection in who is advised by which extension source. Nevertheless, it should be noted that this is all based on the assumption that overall selection is correlated with selection on observables.

In addition to these internal validity concerns, the second limitation of our study relates to external validity. Fruit growers in Switzerland are clearly a highly selective sample of farmers. On the one hand, this has advantages, as these farmers are financially relatively unconstrained and, most importantly, they are well-educated and have relatively homogeneous access to information, including all the different extension services. This might lead one to expect them to be less likely to be influenced by the preferences of their extension service providers than farmers who are less well-educated, have limited access to information, and who have greater financial constraints. On the other hand, it is not clear how far we can extrapolate our findings, e.g. are the same findings, or even more significant findings to be expected among poorer, less educated, and more information-constrained farmers? What role does trust play between advisor and advisee? One of the reasons for choosing the case of *D. Suzukii* in Switzerland is that it is a relatively new threat and there is a lot of uncertainty regarding the threat itself and strategy efficacy. In addition, we do not know if we would find a similar pattern in a case study with less uncertainty, e.g. where both pest and available responses are better understood and in which one might hypothesize that extension services would play a less central role. The finding that public and private extension are associated with distinct strategies to deal with *D. Suzukii* is of interest in the policy making context due to the trend towards the privatization of extension services (Anderson and Feder, 2007, Feder, et al., 2011, Labarthe and Laurent, 2013, Schnyder et al., 2019, Wolf and Zilberman, 2012) and the growing public concern aimed at minimizing the use of pesticides in most countries around the world (Brown, 2018, Lichtenberg and Zimmerman, 1999, Schaub, et al., 2020, Sexton, et al., 2007).

For policy makers, our results imply that in addition to private extension services, it is of vital importance to provide independent, public advice to farmers to ensure that they are able to deliver a wide range of ecosystem services. For example, in the case of pesticide use, this means that potential effects on the environment, human health and the implications of pesticide-resistance must be adequately considered in pest management decisions and extension. This implies that the use of harmful pesticides should be reduced, substituted and/or avoided, and preventive measures should be used as far as economically feasible, taking into account all benefits and costs (private and social). Our results show that public extension can encourage such behavior. However, if preventive measures are to be attractive options, they must be cost-effective. Policy design must pay special attention to this. Generally speaking, the support provided to farmers by independent advisory services is only one of many elements. A holistic approach to agricultural and food policies is needed to reduce risks of pesticide use, e.g. including new technologies and cropping systems, regulatory and policy frameworks as well as economic incentive schemes, such as pesticide taxes (Finger et al., 2017, Möhring et al., 2020a, Pe'Er et al., 2019).

Further research could seek to quantify the impacts of different extension services, not only on the measures adopted, but also on outcomes, e.g. in terms of production, income and environmental damage. Moreover, further research must investigate how the efficiency of the information flow to farmers can be improved, accounting in particular for behavioral factors and heterogeneity (Dessart et al., 2019, Wuepper, 2020). Along these lines, the interdependency between the provision of information, as an element of green nudging, and other policy measures such as taxes and subsidies are a promising area for further research (Chabe-Ferret et al., 2019).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2020.101995.

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