Exploring the pesticide trap: Persistent and Transient pesticide inefficiencies in Swiss winter wheat production

Abstract

This article evaluates total pesticide inefficiency in the case of intensive Swiss wheat producers between 2009 and 2019. The total inefficiency is decomposed into a transient and a structural component. Moreover, we argue that the structural or persistent inefficiency results from path dependency in pesticide use which is also perceived as a 'pesticides trap.' The model is estimated in two steps. In the first step, consistent estimates of the pesticide input requirement are estimated using GMM. The different inefficiency components are obtained from the simulated maximum likelihood in the second step. Our results reveal that there is a high degree of persistent inefficiency when pesticide volume is quantified using load index and active ingredients. However, in the case of the treatment frequency index, we found no evidence of persistent inefficiency.

Keywords: persistent inefficiency, transient inefficiency, path dependency, load index, Swiss wheat

JEL Codes: C51, D24, Q10

Acknowledgment

We would like to thank Agroscope for providing access to the data of the Swiss Agri-Environmental Data Network.

Exploring the pesticide trap: Persistent and Transient pesticide inefficiencies in Swiss winter wheat production

Since World War II, pesticides have been unreluctantly associated with improvements in crop protection. Along with fertilizers, it is one of the critical agricultural inputs related to the increase of food production to face the challenge of an exponentially increasing global population. Pesticides' early effectiveness and relatively low cost have explained their extensive adoption, especially in developed countries. Despite their numerous beneficial effects, as documented in Cooper and Dobson (2007), many adverse effects are attributed to pesticides. These side effects include serious public health problems but also ecosystem deterioration and loss of biodiversity (Bolzonella et al., 2019, Elfikrie et al., 2020, Larsen et al., 2017, Pimentel and Burgess, 2014, Relyea, 2005, Stehle and Schulz, 2015, Tang et al., 2021).[1] Thus the reduction of pesticide risks for humans and the environment is an explicit policy goal in various countries (e.g., Möhring et al. (2020)) and of increasing public awareness (e.g., Schaub et al. (2020)).

Moreover, the overreliance on pesticides has implications for the long-run productivity of agricultural systems. For example, natural processes that govern agroecosystems (e.g., habitats for antagonists of pests) are disrupted, and pest resistance build-up, rendering them even more vulnerable (Savary et al., 2019). In summary, while there is no doubt of the contribution of pesticides to higher agricultural productivity, it remains unclear to what extent structural inefficiencies in pesticide use reduce high productivity in the long run (Antle, 1988 p 1).

[1] Those effects include fertility and reproductive issues, disruption of endocrine systems, and degenerative illnesses regarding human health. Environmental problems comprise contamination of soil, surface, and groundwater with the poisoning of micro-organisms and other vertebras and the decline of bees and pollinators.

In this paper, we quantify the inefficiency of pesticide use and identify structural inefficiencies involved in pesticide use, using panel data from Swiss wheat production. We posit that the existence of pesticides structural or persistent inefficiencies can be perceived as a ‘trap’ that can help explain dependency on pesticides use. Many direct and indirect factors can explain this dependency. Among these factors is pesticide resistance, which appears from long-term exposure to pesticides. Resistance leads to an increase in the dosage and rate of using the less effective pesticide (Popp et al., 2013), creating a vicious dependency circle. In addition, the disappearance of natural enemies has facilitated the emergence of secondary pests, leading farmers to use a broader range of pesticides at high dosage and frequency (Xu et al., 2008). Moreover, the alternatives to pesticides use may be riskier, knowledge-intensive, and require different investments. All these reasons can explain pesticide's structural inefficiency, reflecting a systematic overuse of pesticides.

Previous literature has documented the strong and increasing reliance of the agricultural sector on pesticides that may involve risk for humans and the environment (e.g., Dunn (2012), Enserink et al. (2013), Tang et al. (2021), Varah et al. (2020)). However, large crop production is still lost to pests (Oerke, 2006, Pimentel et al., 1993, Sharma et al., 2017). Pest pressure may even increase due to climate change as, for instance, warming temperatures affect the metabolic rate of insects (Deutsch et al., 2018, Pu et al., 2020). Previous studies have also discussed the possible transition into low- or no-pesticide production systems as well as the difficulties for farmers and other actors (Conway, 2005, Davis et al., 2012, Liu et al., 2014, Möhring and Finger, 2022, Naranjo et al., 2015, Way and van Emden, 2000, Wilson, 2021). An overall remaining observation is that modern agriculture creates a strong path dependency on pesticides once established. This situation may represent a technological 'lock-in' or 'trap' or 'pesticide treadmill,'[2] which reflects a status where producers are increasingly constrained to use pesticides and cannot escape this technology. Cowan and Gunby (1996) framed this observation as 'Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies.' Such lock-in may contradict the general (microeconomic) thinking that market pressures always lead to adopting the most efficient solution, and decisions are reversible if superior alternative solutions are available. The concept of path dependence contrasts with this view, and it describes self-reinforcing mechanisms. It is generally used to explain the adoption of competing technologies that become dominant and suboptimal by excluding superior alternatives[3].

In the literature, the concept of path dependence is the dominant explanation of pesticide use persistency (Cowan and Gunby, 1996). Most of this literature reviews and documents cases in light of theoretical constructs around path dependence[4]. Earlier studies linked this path-dependence to inefficiency. Arthur (1994), for example, shows that one of the properties of a path-dependent process is inefficiency which arises from the inflexibility of adopting better alternatives when they exist or occur. As a result and relating to our case study, such inefficiency will result in a systematic overuse of pesticides compared to the most effective and or efficient level of pesticides use. Pesticides

[2] 'Pesticide treadmill' is characterized by overuse and decreased effectiveness of pesticide due to weakened biological control and appearance of resistance. See Bosch (1978), Brunner (2014), Hedlund et al. (2020), Lichtenberg (2013), Weddle et al. (2009) for more discussion on the pesticide treadmill.

[3] Other papers have looked at the socioeconomic, market, and regulatory (institutions) mechanisms explaining pesticide dependence (Clapp, 2021, Hu, 2020, Wilson and Tisdell, 2001).

[4] These constructs borrow new definitions of path dependence from organizational science and expands over the three phases associated with the concept: preformation phase (origin, triggering events), formation phase (self-reinforcing mechanisms), and path dependence - 'lock-in' - (Page, 2006, Sydow et al., 2009, Vergne and Durand, 2010).

inefficiency was found to be relevant in previous literature. For instance, using Dutch arable farms data between 1989 and 1992, Oude Lansink and Silva (2004) have estimated a high amount of pesticides inefficiency (more than 30%). Using a similar type of data, between 2002 and 2007, Skevas et al. (2012) and Skevas et al. (2014) found an average technical inefficiency of pesticides around 7%. All the previous studies have measured pesticides inefficiency; however, no structural inefficiency has been considered.

We here contribute to this literature by providing a quantitative analysis of the role of pesticides through the lenses of inefficiency. We mainly introduce the notion of the structural inefficiency of pesticides. More specifically, we quantify two types of inefficiencies characterizing pesticide use at the farm level: transient and persistent (Kumbhakar et al., 2014). The transient inefficiency is the most flexible component and can change from one period to another. At the same time, the persistent part expresses the rigidity in inefficiency or a long-term suboptimal technology due to all the mechanisms maintaining in the state of path dependency. In addition, the share of the persistent part in the overall inefficiency may shed some light on the degree of 'entrapment' of producers in pesticide use. Practically, our idea is operationalized by representing the production technology considering a stochastic input requirement frontier model following Guan et al. (2009). In this new representation, pesticide use is expressed as a function of all other inputs and outputs. We adopt a two-step method due to the endogeneity accrued to this representation. In the first step, consistent estimates are obtained using the generalized method of moments (GMM). In the second step, the residuals from the first step are used to disentangle the inefficiency components using maximum simulated likelihood following Filippini and Greene (2016) and Badunenko and Kumbhakar (2016). This is our paper's main contribution, which provides a quantification of the degree of pesticides lock-in. We illustrate our model with a sample of 601 observations from Swiss intensive wheat producers observed over ten years between 2009 and 2018. The sample of Swiss wheat producers is very interesting to exemplify on pesticides dependency as the sector since the beginning of the nineties has undergone big transition into more sustainable production. Two major trends characterized wheat production in Switzerland:

the farms part of the Extenso program which are not allowed to use any type of pesticides except herbicides (Finger and El Benni, 2013, Möhring and Finger, 2022), and the 'conventional' producers. As dependency is not expected to be present in the case of Extenso farms, we have therefore conducted our analysis on the group of intensive wheat farms.

Our results show that evidence of persistent inefficiency is found depending on the pesticide indicators, and in these cases, it is even the higher component of the total inefficiency.

The rest of the article is structured as follows. The following section presents the methodological framework and the two-step model. It is then followed by an application to the case of Swiss winter wheat producers over the period 2009 to 2019. The final section provides a summary of the main findings.

Methodological and econometric framework

We here present a framework on how pesticide is used in crop production processes and the involved inefficiencies. Based on this framework, we develop an econometric framework providing the basis for our empirical analysis. A particular interest of our analysis is to estimate inefficiency and disentangle this into structural and transient inefficiencies. In the case of pesticides, we also argue that structural inefficiency can also be reflected by persistent inefficiency, which is a long-term sub-optimal situation. We show how the persistent inefficiency can be assessed in the next sub-section methodologically.

The Stochastic Input Requirement Frontier

The production possibility frontier (PPF) can be written as

$$H(Y_{it}, Z_{it}, \mathbf{X_{it}}) = 0 \qquad (1)$$

where Y is the output, Z represents pesticide used, and $\mathbf{X}$ the vector of all other inputs. Finally, subscripts $i = 1, \dots, N;\ t = 1, \dots, T_i$ stand for firm (farm) and time. Following Kumbhakar and Hjalmarsson (1998), if (1) satisfies the regularity conditions in Diewert (1974), the production technology can be summarized by the pesticides requirement function showing the level of pesticides needed to produce a specific level of output, which can be expressed as

$$Z_{it} = F(Y_{it}, \mathbf{X_{it}})e^{v_{it}} \tag{2}$$

where v is the random error term, which accounts for factors not in the control of any farm. Next, inefficiency is then incorporated in model (2) as an additional error component. The new model is represented as

$$Z_{it} = F(Y_{it}, \mathbf{X_{it}})e^{v_{it}+u_{it}} \tag{3}$$

Where $u_{it} > 0$ indicates excess in the use of pesticides while $u_{it} = 0$ means that the farm is operating on the frontier. The minimum amount of pesticides given output Y and all the other inputs $\mathbf{X}$ is obtained as

$$Z_{it}^{*} = Z_{it}e^{-u_{it}} = F(Y_{it}, \mathbf{X_{it}})e^{v_{it}} \tag{4}$$

$e^{-u_{it}}$ can be interpreted as Farrell (1957) 's technical efficiency

While representation (3) with two error components has been the cornerstone in the stochastic frontier literature (Kumbhakar and Lovell, 2000), many structural, societal, political problems can systematically create excess pesticides use. We split the inefficiency component into two parts, one persistent and the other transient. The transient inefficiency part still captures issues that can be solved in the short run, e.g., poor management decisions with short-term impact. Moreover, the model is also augmented with a fourth component which captures the farm's latent heterogeneity such as soil quality, climatic conditions, farmers' preferences, or imperfect functioning of credit markets (Colombi et al., 2011). The new model writes as follows

$$Z_{it} = F(Y_{it}, \mathbf{X_{it}})e^{a_i+b_{it}+c_i+w_{it}} \tag{5}$$

$u_{it} = c_i + w_{it}$ is the overall pesticides inefficiency with c_i be the persistent part and w_{it} the transient part, and $v_{it} = a_i + b_{it}$, where a_i is the farm unobserved effects and b_{it} is the random noise.

Econometric framework and implementation

Four-component model estimation

Using the logarithmic transformation and a Cobb-Douglas function, model (5) becomes

$$z_{it} = \lambda y_{it} + \boldsymbol{\beta}'\mathbf{x_{it}} + a_i + b_{it} + c_i + w_{it} \tag{6}$$

Where $z_{it} = \ln Z_{it}$, $y_{it} = \ln Y_{it}$, $\mathbf{x_{it}} = \ln \mathbf{X_{it}}$, and $\boldsymbol{\beta}$ is a parameter vector. Model (6) is a typical four-component stochastic frontier model which has been discussed in Colombi et al. (2014), Kumbhakar et al. (2014), Tsionas and Kumbhakar (2014). From model 6, we can obtain the composed error term as $\epsilon_{it} = a_i + b_{it} + c_i + w_{it}$. These error terms are assumed to be distributed independently and identically and independently from each other. In particular, we have $a_i = \sigma_a A_i$ and $b_{it} = \sigma_b B_{it}$, and $c_i = \sigma_c |C_i|$, $w_{it} = \sigma_w |W_{it}|$ with $C_i \sim \mathcal{N}(0,1)$, $W_{it} \sim \mathcal{N}(0,1)$, $A_i \sim \mathcal{N}(0,1)$, and $B_{it} \sim \mathcal{N}(0,1)$ respectively. A tractable full information likelihood is obtained in Colombi et al. (2014), who used the properties of the Closed-Skewed Normal distribution. However, this likelihood is very hard to estimate because of the multivariate integrals involved.[5] Therefore, in this article, we follow Filippini and Greene (2016) and use maximum simulated likelihood, which is easier to estimate.

Let$'s$ re-write model (6) as follows:

$$z_{it} = \lambda y_{it} + \boldsymbol{\beta}'\mathbf{x_{it}} + \theta_i + b_{it} + w_{it} \tag{7}$$

[5] See Appendix A.

where $\theta_i = \sigma_a A_i + \sigma_c |C_i|$. Conditioned on θ_i, the T_i observations for farm i are independent. The conditional density is obtained from the derivation of the convolution of the normal and half-normal distributions. We have

$$f(\mu_{i1}, \dots, \mu_{iT_i} | \theta_i) = \prod_{t=1}^{T_i} \frac{2}{\sqrt{\sigma_b^2 + \sigma_w^2}} \phi\left(\frac{\mu_{it}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) \Phi\left(\frac{\mu_{it}\frac{\sigma_w}{\sigma_b}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) \tag{8}$$

Where $\mu_{it} = z_{it} - \lambda y_{it} - \mathbf{\beta}'\mathbf{x_{it}} - \theta_i$. ϕ is the standard normal density, and Φ is the standard normal cdf. The unconditional log-likelihood for the model is obtained by integrating the unobserved random variable, θ_i out of the previous conditional density. Thus,

$$f(\mu_{i1}, \dots, \mu_{iT_i}) = \int_{\theta_i}^{\infty} \prod_{t=1}^{T_i} \frac{2}{\sqrt{\sigma_b^2 + \sigma_w^2}} \phi\left(\frac{\mu_{it}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) \Phi\left(\frac{\mu_{it}\frac{\sigma_w}{\sigma_b}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) p(\theta_i) d\theta_i \tag{9}$$

Where

$$p(\theta_i) = \frac{2}{\sqrt{\sigma_a^2 + \sigma_c^2}} \phi\left(\frac{\sigma_a A_i + \sigma_c |C_i|}{\sqrt{\sigma_a^2 + \sigma_c^2}}\right) \Phi\left(\frac{(\sigma_a A_i + \sigma_c |C_i|)\frac{\sigma_c}{\sigma_a}}{\sqrt{\sigma_a^2 + \sigma_c^2}}\right) \tag{10}$$

Then

$$\log L(\lambda, \mathbf{\beta}, \sigma_a, \sigma_b, \sigma_c, \sigma_w) = \sum_{i=1}^{N} \log f(\mu_{i1}, \dots, \mu_{iT_i}) \tag{11}$$

The integral in (9) has no closed-form, but simulation can evaluate it. The simulated log-likelihood is

$$\begin{aligned} &\log L(\lambda, \mathbf{\beta}, \sigma_a, \sigma_b, \sigma_c, \sigma_w) \\ &= \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \frac{2}{\sqrt{\sigma_b^2 + \sigma_w^2}} \phi\left(\frac{\mu_{itr}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) \Phi\left(\frac{\mu_{itr}\frac{\sigma_w}{\sigma_b}}{\sqrt{\sigma_b^2 + \sigma_w^2}}\right) \end{aligned} \tag{12}$$

where $\mu_{itr} = z_{it} - \lambda y_{it} - \mathbf{\beta}'\mathbf{x_{it}} - \sigma_a A_{ir} - \sigma_c |C_{ir}|$

The simulation requires pairs of random draws (A_{ir} & C_{ir}) from two standard normal distributions. For efficient computation, the Halton sequence of draws is considered. The conditional efficiencies still use some results from Colombi et al. (2014) and are based on the moment generating function for the closed-skewed normal distribution.[6] Moreover, following Kumbhakar et al. (2014), a total efficiency measure can be obtained as

$$\text{total efficiency}_{\text{it}} = E[\exp(-c_i)|\epsilon_{it}] \times E[\exp(-w_{it})|\epsilon_{it}] \tag{13}$$

where $E[\exp(-c_i)|\epsilon_{it}]$ represents the persistent conditional efficiency while $E[\exp(-w_{it})|\epsilon_{it}]$ is the conditional transient efficiency.

The estimation of the model (6) may be flawed because of the endogeneity of the output and some of the inputs. This endogeneity can come from multiple sources: i- correlation between (y, x) and the unobserved heterogeneity a, ii-) correlation between (y, x) and the persistent inefficiency c,[7] iii-) correlation between (y, x) and the random noise b, -iv) correlation between (y, x) and the transient inefficiency w, or v-) any combination of the previous correlations.

Two-step procedure for endogeneity correction

To deal with the endogeneity, we consider a two-step approach procedure. In the first step, a transformation is used to eliminate the time-invariant components $(a_i + c_i)$. Practically, since our panel data contains some gaps, and following Arellano and Bover (1995), we retained the forward-orthogonal deviations. We opted for this approach instead of the first-difference transformation, as the latter magnifies gaps in the unbalanced panel, while the forward-orthogonal deviations preserve the sample size. Applied to a variable, the forward-orthogonal deviations subtract from the current

[6] See Appendix B.

[7] Mundlak (1961), Mundlak and Hoch (1965) argued that omitting the unobserved time-invariant management (either farm effect or persistent inefficiency) creates endogeneity bias because it is likely to be correlated with the inputs.

value, the average of all future available observations. Forward-orthogonal deviations are always computable for all observations except the last for each cross-section. The transformed model is

$$\widetilde{\Delta}_t z_{it} = \lambda\widetilde{\Delta}_t y_{it} + \boldsymbol{\beta}'\widetilde{\boldsymbol{\Delta}}_{\mathbf{t}}\mathbf{x}_{\mathbf{it}} + \widetilde{\Delta}_t \epsilon_{it} \qquad (14)$$

where $\widetilde{\Delta}_t \epsilon_{it} = \widetilde{\Delta}_t b_{it} + \widetilde{\Delta}_t w_{it}$.

The forward-orthogonal deviations transformation matrix is[8]

$$\mathbf{H_i} = \mathrm{diag}\left(\sqrt{\frac{T_i}{T_i-1}}, \sqrt{\frac{T_i-1}{T_i-2}}, \dots, \sqrt{\frac{2}{1}}\right) \times \begin{pmatrix} \frac{T_i-1}{T_i} & -\frac{1}{T_i} & -\frac{1}{T_i} & \cdots & -\frac{1}{T_i} & -\frac{1}{T_i} \\ 0 & \frac{T_i-2}{T_i-1} & -\frac{1}{T_i-1} & & -\frac{1}{T_i-1} & -\frac{1}{T_i-1} \\ & \vdots & & \ddots & & \vdots \\ & 0\quad 0\quad 0 & & \cdots & \frac{1}{2} & -\frac{1}{2} \end{pmatrix} \qquad (15)$$

After eliminating the time-invariant component, we consistently estimate the parameters $(\lambda, \boldsymbol{\beta})$ in the frontier function using the GMM approach. We consider the following moment conditions:

- In the case of a strictly exogenous variable k, we have

$$E\left[k_{i,t-s}\widetilde{\Delta}_t \epsilon_{it}\right] = 0 \qquad t-s = 0, 1, \dots, T\,; t = s, \dots, T-1$$

- When the variable k is predetermined or weakly exogenous, we have:

$$E\left[k_{i,t-s}\widetilde{\Delta}_t \epsilon_{it}\right] = 0 \qquad s = 0, 1, \dots, t\,; t = s, \dots, T-1$$

- Finally, in the case k is an endogenous variable, we have

$$E\left[k_{i,t-s}\widetilde{\Delta}_t \epsilon_{it}\right] = 0 \qquad s = 1, \dots, T\,; t = s, \dots, T-1$$

[8] The first part of the matrix is a scaling that ensures that the variance remains unchanged if ϵ_{it} is homoskedastic

When all the instruments are stacked together[9], we obtain:

$$E[\mathbf{K_i}'\mathbf{H_i}\boldsymbol{\epsilon}_\mathbf{i}] = E[\mathbf{m_i}(\boldsymbol{\Theta})] = 0 \tag{16}$$

where $\boldsymbol{\Theta} = (\lambda, \boldsymbol{\beta})'$

The GMM estimator minimizes a quadratic form

$$\widehat{\boldsymbol{\Theta}} = \arg\min_{\boldsymbol{\Theta}} \left(\frac{1}{N}\sum_i \mathbf{M_i}'\mathbf{H_i}\boldsymbol{\epsilon}_\mathbf{i}\right)' \mathbf{W} \left(\frac{1}{N}\sum_i \mathbf{M_i}'\mathbf{H_i}\boldsymbol{\epsilon}_\mathbf{i}\right) \tag{17}$$

where N is the sample size, and $\mathbf{W}$ is a weighting matrix. An optimal weighting matrix is given by

$$\mathbf{W}(\widetilde{\boldsymbol{\Theta}}) = \left(\frac{1}{N}\sum_i \mathbf{m_i}(\widetilde{\boldsymbol{\Theta}})\mathbf{m_i}(\widetilde{\boldsymbol{\Theta}})'\right)^{-\mathbf{1}}$$

where $\widetilde{\boldsymbol{\Theta}}$ is obtained from an initial GMM with a different weighting matrix (Arellano and Bond, 1991). Our model includes time effects through year dummies to account for global shocks. Without loss of generality, the year dummies are strictly exogenous, and the following level moment conditions can be used:

$$E[\mathbf{D_i}'\boldsymbol{\epsilon}_\mathbf{i}] = 0 \tag{18}$$

where $\boldsymbol{\epsilon}_\mathbf{i} = \mathbf{z_i} - \lambda\mathbf{y_i} - \boldsymbol{\beta}'\mathbf{x_i} - \boldsymbol{\delta}'\mathbf{D_i}$ and $\mathbf{D_i}$ a matrix of year dummies. (18) and (20) imply two sets of moment conditions, one with a transformed error term and the other with a level error term. These

[9] Building upon Arellano and Bover (1995), we use lagged explanatory variables as instruments. As Wang and Bellemare (2019 p 2) underline, this is a valid approach[9] when “lagged explanatory variables have no direct causal effect on the dependent variable or on the unobserved confounders.” Moreover, in our case, lag of exogenous non-explanatory variables is also used.

two sets of moments conditions particularly relate to the system GMM approach discussed in Blundell and Bond (1998). The new stacked moment condition is

$$E[\mathbf{m_i}(\mathbf{\Theta})] = E\begin{bmatrix}\mathbf{K_i}'\widetilde{\mathbf{\Delta}}_\mathbf{t}\boldsymbol{\epsilon}_\mathbf{i}\\ \mathbf{D_i}'\boldsymbol{\epsilon}_\mathbf{i}\end{bmatrix} = 0 \tag{19}$$

where $\widetilde{\mathbf{\Delta}}_\mathbf{t}\boldsymbol{\epsilon}_\mathbf{i} = \widetilde{\mathbf{\Delta}}_\mathbf{t}\,\mathbf{z_i} - \lambda\widetilde{\mathbf{\Delta}}_\mathbf{t}\mathbf{y_i} - \boldsymbol{\beta}'\widetilde{\mathbf{\Delta}}_\mathbf{t}\mathbf{x_i}$ and $\mathbf{\Theta}$ now also includes the parameter δ_t.

An alternative formulation of the moment of conditions allows a simultaneous estimation using a level GMM (Arellano and Bover, 1995):

$$E\begin{bmatrix}\mathbf{K_i}'\widetilde{\mathbf{\Delta}}_\mathbf{t}\boldsymbol{\epsilon}_\mathbf{i}\\ \mathbf{D_i}'\boldsymbol{\epsilon}_\mathbf{i}\end{bmatrix} = E\begin{bmatrix}\mathbf{K_i}'\mathbf{H_i}\boldsymbol{\epsilon}_\mathbf{i}\\ \mathbf{D_i}'\boldsymbol{\epsilon}_\mathbf{i}\end{bmatrix} = E\left[\begin{pmatrix}\mathbf{K_i}'\mathbf{H_i}\\ \mathbf{D_i}'\end{pmatrix}\boldsymbol{\epsilon}_\mathbf{i}\right] = 0 \tag{20}$$

For the estimation, we have retained an initial weighting matrix that is identical to a 2SLS (Windmeijer, 2000):

$$\mathbf{W_1} = \left(\frac{1}{N}\sum_i \begin{pmatrix}\mathbf{K_i}'\mathbf{H_i}\mathbf{H_i}'\mathbf{K_i} & \mathbf{K_i}'\mathbf{H_i}\mathbf{D_i}\\ \mathbf{D_i}'\mathbf{H_i}'\mathbf{K_i} & \mathbf{D_i}'\mathbf{D_i}\end{pmatrix}\right)^{-1} \tag{21}$$

The standard errors obtained with the GMM estimates tend to be severely downward biased. Windmeijer (2005) suggested a finite-sample correction which is applied in this paper.[10] Finally, the orthogonality of the instruments to the error terms is evaluated using Sargan's overidentification test.

Given the consistent estimates of $(\hat{\lambda}, \hat{\boldsymbol{\beta}}, \hat{\delta})'$, in a second step the remaining parameters are estimated using the maximum simulated likelihood (MSL) as described in the previous subsection. In particular, the MSL is applied to the equation

$$\hat{\epsilon}_{it} = \boldsymbol{\alpha}'\mathbf{Q}_i + a_i + b_{it} + c_i + w_{it} \tag{22}$$

[10] The corrected standard errors are still biased but less severely.

where $\hat{\epsilon}_{it}$ are the residuals from the first step and $\mathbf{Q_i}$ a vector of time-invariant variables. Estimation of (22) will help to disentangle the persistent and the transient inefficiency, and the contribution of each type of inefficiency in the overall inefficiency can be estimated.

Data on Swiss winter wheat producers

This section illustrates the case study used from Swiss wheat production. We base our analysis on a sample of wheat producers observed over ten years between 2009 and 2018. The dataset used for this analysis is provided by the Swiss center of excellence for agricultural research (Agroscope) under the project "Central Evaluation of Agri-Environmental Indicators" (CE-AEI) (de Baan et al., 2020). The Swiss wheat production has the particularity of being categorized into two major groups: Intensive vs. Extenso. The latter group concerns farmers where pesticide use is limited to herbicides and seed treatments. In other words, fungicides, insecticides, plant growth regulators, and chemical-synthetic stimulators of natural resistance are not allowed (Finger and El Benni, 2013). Moreover, farmers enrolled in the Extenso program have to face additional constraints in terms of sustainability and compulsory crop rotation (Möhring and Finger, 2022). For this reason, our analysis only focuses on intensive farms as they are more susceptible to show some structural inefficiency in pesticide use.

Swiss wheat producers' data

The data enables us to provide detailed information on input use and crop management. For example, we can identify if and how (e.g., with which technology) specific management practices such as tillage, seeding, mechanical weed management, fertilization, and pesticide application, were done. We transform this information in comparable units, i.e., to transform machinery use and labor force into

Swiss Francs[11]. Descriptive statistics of all the variables considered for this analysis are presented in Table 1.[12] The output variable is the total wheat production measured in tons. Five inputs variables are shown in Table 1. Nitrogen use in kilograms, labor and machinery costs deflated to December 2015 Swiss Francs (CHF), mechanical weeding costs (also deflated CHF), wheat surface, and finally pesticides use. We use three indicators to express pesticide use. First, the quantity of active ingredients in kg (AI). Second, we use the treatment frequency index (TFI) that measures pesticides intensity relatively to standard dose rates of active ingredients. Third, we aim to account also for pesticide risks for the environment and human health that differ per type of pesticides and are not necessarily related to quantities (e.g., Möhring et al. (2019)). More specially, we use the pesticide load index (LI) used to quantify potential risks of pesticide use over three indicators: human health, ecotoxicology, and environmental fate (Möhring et al., 2021) to transform individual pesticide applications into a Load Indicator each year.

[11] More specifically, we use Swiss machinery costs data and detailed assumptions on labor requirements for specific crop management practices (e.g. Gazzarin and Lips (2013), Heitkämper et al. (2019)) The code used in this transformation can be found here https://github.com/AECP-ETHZ/ZA-AUI.

[12] See Appendix C for descriptive statistics of Extenso farms.

Table 1: Summary Statistics of intensive wheat production in Swiss farms between 2009-2018

	Main Model variables	
Variables	Mean	St. Dev.
Wheat production (dt) Y	398.2	309.2
Pesticides Load index (LI) Z	12.3	18.5
Active Ingredients (AI) Z	9.8	11.2
Treatment Frequency Index (TFI) Z	2.6	1.5
Nitrogen use (kilograms) X_1	931.7	793.0
Labor and machinery costs (constant CHF) X_2	7,200	5,477
Mechanical weeding (constant CHF) X_3	1,576	1,642
Wheat surface (hectares) X_4	6.2	4.6
Wheat price per dt (CHF)	45.9	6.3
Pesticides price (CHF/active ingredient)	4,231	34,038
	Other additional variables	
Wheat yield (tons/hectare)	6.3	-
Pesticides Load index per hectare	1.89	-
Active Ingredients per hectare	1.55	-
Nitrogen use (kilograms/hectare)	146	-
Labor and machinery costs per hectare	1162	-
Mechanical weeding per hectare	282	-
Wheat revenues (constant CHF/hectare)	2841	-
Number of observations	601	-

Source: CE-AEI and authors' computations.
Note: Monetary values are expressed in December 2015 Swiss Francs (CHF)

In comparison to Extenso farms, additional variables in Table 1 and Appendix C show that Intensive farms have a higher yield. Despite the higher wheat price premium for Extenso farms, the lower yield is also reflected in the lower wheat revenues per hectare. As expected, Extenso farms use less chemical input per hectare (lower load index and active ingredients) and a lower treatment frequency index than Intensive farms. Since 1993, the Swiss government has subsidized low-input farming under the

Extenso program. The prerogative of this program is the implementation of an integrated pest management system where mainly insecticides and fungicides are banned. In exchange, farmers receive additional subsidies to compensate for yield losses. This compensation amounts to 400 CHF/hectare[13], which, when included in the revenue per hectare of Extenso farms, raises to an average of 3,048 constant CHF per hectare, about 7% higher than Intensive farms revenue per hectare. As herbicides are forbidden for Extenso farms, the figures in Appendix C show that these farms resort more to mechanical weeding than Intensive farms. Regarding other inputs, the fertilizers used per hectare are almost equivalent between both groups of farms. In contrast, labor and machinery expenses per hectare are higher in the group of Intensive farms.

Model estimation and results

The input requirement function in (5) is estimated using a Cobb-Douglas specification. The log-linearization of the function is possible for all the variables except mechanical weeding, for which zero values are present. For this variable, we use the inverse hyperbolic sine transformation ($\tilde{x} = \ln\left(x + \sqrt{x^2 + 1}\right)$ (Bellemare and Wichman, 2020). One caveat of the inverse hyperbolic sine transformation is the dependence on units of measurement. To minimize this issue, we follow the iterative process suggested by Aihounton and Henningsen (2021) to find the appropriate magnitude of the data. In our case, mechanical weeding is transformed into thousands of CHF.

For the GMM estimation, we are concerned about the endogeneity of the output (Y) and mechanical weeding (X_3). We suspect that the level of pesticides and output is decided simultaneously, in addition to mechanical weeding, which is a substitute for herbicides. All the other inputs (nitrogen, labor,

[13] https://www.fedlex.admin.ch/eli/cc/2013/765/fr#annex_7/lvl_d4e347/lvl_5/lvl_d4e367

machinery expenses, and planted area) are treated as weakly exogenous (predetermined).[14] We have also considered two external and strictly exogenous variables: wheat and pesticide prices. Moreover, to avoid instruments proliferation, we have restricted the lag length to three based on the average time of presence of each farm and the lead to two in the case of exogenous variables. Finally, we collapse all the instruments (Roodman, 2009).

The (two-step) GMM estimates are provided in Table 2 for the three different measures of pesticides.[15] The Sargan overidentification test indicates that the orthogonality conditions are satisfied in all the three models presented with p-values higher than 0.21. When load index (LI) and active ingredients (AI) are the dependent variables, no variables appear to be significant. However, in the case of the treatment frequency index (TFI), wheat production has a significant positive effect while the production area has a significant negative impact. These results are intuitive as for these types of farms, higher production is associated with increased use of pesticides. Moreover, intensifying also allows these farms to use pesticides to increase their yield and, therefore, require less area for producing the same amount. It is worth noting that many variables lose their significativity when the farms' effects are included in the model.

We have also estimated the GMM model for the Extenso farms and the pooled sample for comparison purposes. Results can be found in Appendix E. In the case of Extenso farms, we found a significant and negative effect of mechanical weeding in the cases where load index (LI) and active ingredients (AI) are the dependent variables. This again stresses the importance of mechanical weeding in Extenso

[14] We consider nitrogen, labor and machinery expenses, area planted as predetermined in our estimation as we assume that these variables in period t are uncorrelated with the error term in period t but correlated with past error terms. This implies that we assume that many unobserved factors that explain past pesticides use decisions affect the current level of these variables.

[15] See Appendix D for the full table of results.

farms. In the case of the treatment frequency index (TFI) no variables appear to be significant. We recommend taking these results with caution as the Extenso program is voluntary, which might be the source of selection bias ignored in the results presented in Appendix E. In the case of the pooled sample, for all pesticide indicators, the labor and machinery costs (both excluding mechanical weed control) are positively and significatively related to pesticide use. This implies that the two input variables are complements rather than substitutes. A potential reason for this complementarity is that pesticide applications also require machinery and labor inputs. In contrast, we find mechanical weeding to be a substitute for pesticides in the case of LI and AI as pesticide indicators (like in Extenso farms). When TFI is considered, mechanical weeding is non-significant.

The MSL results of the second stage estimation are presented in Table 3.[16] For some of the estimates, the algorithm fails to derive elements of the inverse Hessian matrix regarding the persistent inefficiency component σ_c^2, suggesting a model without this component. The results in Table 4 point to persistent pesticide inefficiency when load index and active ingredients are the pesticide indicators. In the case of the treatment frequency index, we found no evidence of persistent inefficiency. Moreover, persistent efficiency is even lower than transient efficiency whenever it exists. For the Intensive farms, it seems that the pesticide indicator used might point to different conclusions in terms of inefficiencies. As previously, we have also estimated the model for the Extenso and the pooled sample (Appendix F). As hypothesized, we found no persistent pesticide inefficiency in the case of Extenso farms in all cases. In the case of the pooled sample, of the three pesticide indicators, only the load and the treatment frequency indices reveal the presence of persistent inefficiency.

Table 5 presents the share of pesticides persistent inefficiency in the total inefficiency. This share is computed by taking the logarithmic transformation of formula (13). The results in this Table reveal that when it exists, the persistent part of the inefficiency is the significant component of the overall

[16] Results for Extenso farms and the pooled sample can be found in Appendix F.

performance, and it is on average about 84% of the pesticide's total inefficiency. The distributions of the shares are very similar in all cases. As argued in the introduction section, this share can reflect the degree of entrapment of producers regarding pesticides use. It appears here to be very high.

Table 2: GMM Estimation Results of the First-Step Model

Variables	LI	AI	TFI
Wheat Production (Y)	2.06	4.28	**1.68****
	(1.95)	(3.31)	(0.85)
Nitrogen (x_1)	0.27	0.38	0.08
	(0.42)	(0.44)	(0.18)
Labor and machinery costs (x_2)	0.43	0.60	0.89
	(1.12)	(1.47)	(0.62)
Mechanical weeding costs (x_3)	-0.77	-0.50	-0.22
	(0.50)	(0.54)	(0.36)
Production surface (x_4)	-1.75	-4.20	**-2.49*****
	(1.86)	(2.97)	(0.80)
Year Effects	yes	yes	yes
Farms Effects	yes	yes	yes
Number of instruments	40	40	40
Sargan Statistic	30.44	29.87	30.45
Sargan test p-value	0.21	0.23	0.21

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: lower-case letters y, x_1, x_2, x_4 represents logarithms of Y, X_1, X_2, X_4 respectively and x_3 is the IHS transformation of X_3. Parameters standard errors are in brackets.

Table 3: Persistent and Transient Efficiency Model (Second-Step)

	LI	*AI*	*TFI*
(Intercept)	-0.08	-0.49	-0.02
	(0.28)	(0.29)	(0.11)
Kantonal dummies	Yes	Yes	Yes
$\ln \lambda = \ln \frac{\sigma_w}{\sigma_b}$	-5.37	-4.62	-3.93
	(15.13)	(6.96)	(3.59)
$\ln \sigma = \ln \sqrt{\sigma_w^2 + \sigma_b^2}$	0.30^{***}	0.32^{***}	-0.57^{***}
	(0.02)	(0.02)	(0.03)
$\ln \sigma_a^2$	-0.52^{***}	-0.87^{*}	-1.38^{***}
	(0.13)	(0.39)	(0.21)
$\ln \sigma_c^2$	**-1.33^{*}**	**-0.35°**	-30.62
	(0.52)	(0.19)	NA
Mean Persistent Efficiency	0.71	0.60	1.00
Mean Transient Efficiency	0.94	0.91	0.92
Mean Total Efficiency	0.67	0.54	0.92

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Note: Parameters standard errors are in brackets.

Table 4: Share of Persistent Inefficiency distribution in Total Inefficiency

	LI	AI
Min	0.74	0.72
1st Quartile	0.83	0.82
Median	0.85	0.85
Mean	0.84	0.84
3rd Quartile	0.86	0.87
Max	0.90	0.95

Conclusion

In this paper, we explore the matter of pesticides trap in the case of Swiss winter wheat producers. Our analysis is grounded on the assumption that self-reinforcing mechanisms that are the main features of a trap or path dependency place farms in a sub-optimal state characterized by persistent inefficiency in pesticide use. We first estimate an input requirement technology to disentangle persistent inefficiency from transitory inefficiency in pesticide use. After correcting for potential endogeneity issues, persistent and transient inefficiency are estimated using maximum simulated likelihood. The results of intensive Swiss winter wheat producers reveal mixed results depending on the pesticide indicators used. When load index and active ingredients are considered, we found a very high level of persistent inefficiency, representing more than 84% of the total pesticide inefficiency. In the case of the treatment frequency index, there was no evidence of persistent inefficiency. Overall, these results point out the different implications of different pesticides indicators, as already underlined in Möhring et al. (2019)

From a policy perspective, our results raise the question of path dependency for intensive wheat producers. Looking at the parallel in the "poverty trap" literature, an exogenous chock (e.g., in terms of stringent or not voluntary policy regulation) may be necessary to break this pesticide dependence.

In addition, it seems that the Extenso program may provide effective incentives in overcoming self-reinforcing mechanisms that may lead to path dependency. Thereby, our results encourage strengthening the Extenso program.

Future research can examine three things. First, assess the influence of pesticides lock-in features, as described in the literature, in explaining the levels of inefficiency. Second, our analysis covers only a specific case study so that more evidence-based on other agricultural systems is needed. Finally, the question of which pesticide indicators to consider is also raised by this work as depending on the pesticide indicator, different conclusions can be formulated. One can imagine that a specific pesticide indicator may better fit a particular type of farm.

References

Aigner, D., C.A.K. Lovell, and P. Schmidt. 1977. "Formulation and estimation of stochastic frontier production function models." *Journal of econometrics* 6:21-37.

Aihounton, G.B.D., and A. Henningsen. 2021. "Units of measurement and the inverse hyperbolic sine transformation." *The Econometrics Journal* 24:334-351.

Antle, J.M. 1988. *Pesticide Policy, Production Risk, and Producer Welfare: An Econometric Approach to Applied Welfare Economics*: Taylor & Francis.

Arellano, M., and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies* 58:277-297.

Arellano, M., and O. Bover. 1995. "Another look at the instrumental variable estimation of error-components models." *Journal of econometrics* 68:29-51.

Arthur, W.B. 1994. *Increasing returns and path dependence in the economy*: University of michigan Press.

Azzalini, A. 2013. *The Skew-Normal and Related Families*. Cambridge: Cambridge University Press.

Badunenko, O., and S.C. Kumbhakar. 2017. "Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: Do ownership, regulation and heterogeneity matter?" *European Journal of Operational Research* 260:789-803.

---. 2016. "When, where and how to estimate persistent and transient efficiency in stochastic frontier panel data models." *European Journal of Operational Research* 255:272-287.

Bellemare, M.F., and C.J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics* 82:50-61.

Blundell, R., and S. Bond. 1998. "Initial conditions and moment restrictions in dynamic panel data models." *Journal of econometrics* 87:115-143.

Bolzonella, C., M. Lucchetta, G. Teo, V. Boatto, and A. Zanella. 2019. "Is there a way to rate insecticides that is less detrimental to human and environmental health?" *Global Ecology and Conservation* 20:e00699.

Bosch, R.V.D. 1978. *The Pesticide Conspiracy*: University of California Press.

Brunner, J.F. (2014) "Integrated Pest Management in Tree Fruit Crops." In N.K. Van Alfen ed. *Encyclopedia of Agriculture and Food Systems.* Oxford, Academic Press, pp. 15-30.

Clapp, J. 2021. "Explaining Growing Glyphosate Use: The Political Economy of Herbicide-Dependent Agriculture." *Global Environmental Change* 67:102239.

Colombi, R., S.C. Kumbhakar, G. Martini, and G. Vittadini. 2014. "Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency." *Journal of Productivity Analysis* 42:123-136.

Colombi, R., G. Martini, and G. Vittadini. 2011. "A stochastic frontier model with short-run and long-run inefficiency random effects."

Conway, G. (2005) "The doubly-green revolution." In J. Pretty ed. *The Earthscan reader in sustainable agriculture.* pp. 115-127.

Cooper, J., and H. Dobson. 2007. "The benefits of pesticides to mankind and the environment." *Crop Protection* 26:1337-1348.

Cowan, R., and P. Gunby. 1996. "Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies." *The economic journal* 106:521-542.

Davis, A.S., J.D. Hill, C.A. Chase, A.M. Johanns, and M. Liebman. 2012. "Increasing Cropping System Diversity Balances Productivity, Profitability and Environmental Health." *PLoS ONE* 7:e47149.

de Baan, L., J.F. Blom, and O. Daniel. 2020. "Pflanzenschutzmittel im Feldbau: Einsatz und Gewässerrisiken von 2009 bis 2018." *Agrarforschung Schweiz* 11:162-174.

Deutsch, C.A., J.J. Tewksbury, M. Tigchelaar, D.S. Battisti, S.C. Merrill, R.B. Huey, and R.L. Naylor. 2018. "Increase in crop losses to insect pests in a warming climate." *Science* 361:916.

Diewert, W.E. 1974. "Functional Forms for Revenue and Factor Requirements Functions." *International Economic Review* 15:119-130.

Dunn, R. 2012. "In retrospect: Silent Spring." *Nature* 485:578-579.

Elfikrie, N., Y.B. Ho, S.Z. Zaidon, H. Juahir, and E.S.S. Tan. 2020. "Occurrence of pesticides in surface water, pesticides removal efficiency in drinking water treatment plant and potential health risk to consumers in Tengi River Basin, Malaysia." *Science of the Total Environment* 712:136540.

Enserink, M., P.J. Hines, S.N. Vignieri, N.S. Wigginton, and J.S. Yeston. 2013. "The Pesticide Paradox." *Science* 341:728.

Farrell, M.J. 1957. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society Series a-General* 120:253-290.

Filippini, M., and W. Greene. 2016. "Persistent and transient productive inefficiency: a maximum simulated likelihood approach." *Journal of Productivity Analysis* 45:187-196.

Finger, R., and N. El Benni. 2013. "Farmers' adoption of extensive wheat production – Determinants and implications." *Land Use Policy* 30:206-213.

Gazzarin, C., and M. Lips. 2013. "Berechnung und Grunddaten der Maschinenkosten." *Maschinenkostenbericht, Juni*:33.

Guan, Z.F., S.C. Kumbhakar, R.J. Myers, and A.O. Lansink. 2009. "Measuring Excess Capital Capacity in Agricultural Production." *American Journal of Agricultural Economics* 91:765-776.

Hedlund, J., S.B. Longo, and R. York. 2020. "Agriculture, Pesticide Use, and Economic Development: A Global Examination (1990–2014)." *Rural Sociology* 85:519-544.

Heitkämper, K., J. Lutz, and R. Stark. 2019. "Identifier et planifier la charge de travail dans l'exploitation et la famille." *Recherche agronomique suisse*:110.

Hu, Z. 2020. "What Socio-Economic and Political Factors Lead to Global Pesticide Dependence? A Critical Review from a Social Science Perspective." *International Journal of Environmental Research and Public Health* 17.

Kumbhakar, S.C., and L. Hjalmarsson. 1998. "Relative performance of public and private ownership under yardstick competition: electricity retail distribution." *European Economic Review* 42:97-122.

Kumbhakar, S.C., G. Lien, and J.B. Hardaker. 2014. "Technical efficiency in competing panel data models: a study of Norwegian grain farming." *Journal of Productivity Analysis* 41:321-337.

Kumbhakar, S.C., and C.A.K. Lovell. 2000. *Stochastic Frontier Analysis*: Cambridge University Press.

Larsen, A.E., S.D. Gaines, and O. Deschênes. 2017. "Agricultural pesticide use and adverse birth outcomes in the San Joaquin Valley of California." *Nature Communications* 8:302.

Lichtenberg, E. (2013) "Economics of Pesticide Use and Regulation." In J.F. Shogren ed. *Encyclopedia of Energy, Natural Resource, and Environmental Economics.* Waltham, Elsevier, pp. 86-97.

Liu, X., M. Chen, H.L. Collins, D.W. Onstad, R.T. Roush, Q. Zhang, E.D. Earle, and A.M. Shelton. 2014. "Natural Enemies Delay Insect Resistance to Bt Crops." *PLoS ONE* 9:e90366.

Meeusen, W., and J. Vandenbroeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18:435-445.

Möhring, N., and R. Finger. 2022. "Pesticide-free but not organic: Adoption of a large-scale wheat production standard in Switzerland." *Food Policy* 106:102188.

Möhring, N., S. Gaba, and R. Finger. 2019. "Quantity based indicators fail to identify extreme pesticide risks." *Science of the Total Environment* 646:503-523.

Möhring, N., K. Ingold, P. Kudsk, F. Martin-Laurent, U. Niggli, M. Siegrist, B. Studer, A. Walter, and R. Finger. 2020. "Pathways for advancing pesticide policies." *Nature Food* 1:535-540.

Möhring, N., P. Kudsk, L.N. Jørgensen, J.E. Ørum, and R. Finger. 2021. "An R package to calculate potential environmental and human health risks from pesticide applications using the 'Pesticide Load' indicator applied in Denmark." *Computers and Electronics in Agriculture* 191:106498.

Mundlak, Y. 1961. "Empirical Production Function Free of Management Bias." *Journal of Farm Economics* 43:44-56.

Mundlak, Y., and I. Hoch. 1965. "Consequences of Alternative Specifications in Estimation of Cobb-Douglas Production Functions." *Econometrica* 33:814-828.

Naranjo, S.E., P.C. Ellsworth, and G.B. Frisvold. 2015. "Economic Value of Biological Control in Integrated Pest Management of Managed Plant Systems." *Annual review of entomology* 60:621-645.

Oerke, E.C. 2006. "Crop losses to pests." *The Journal of Agricultural Science* 144:31.

Oude Lansink, A., and E. Silva. 2004. "Non-parametric production analysis of pesticides use in the Netherlands." *Journal of Productivity Analysis* 21:49-65.

Page, S.E. 2006. "Path Dependence." *Quarterly Journal of Political Science* 1:87-115.

Pimentel, D., and M. Burgess (2014) "Environmental and Economic Costs of the Application of Pesticides Primarily in the United States." In *Integrated Pest Management.* Springer, pp. 47-71.

Pimentel, D., L. McLaughlin, A. Zepp, B. Lakitan, T. Kraus, P. Kleinman, F. Vancini, W.J. Roach, E. Graap, W.S. Keeton, and G. Selig (1993) "Environmental and Economic Impacts of Reducing U.S. Agricultural Pesticide Use." In D. Pimentel, and H. Lehman eds. *The Pesticide Question: Environment, Economics, and Ethics.* Boston, MA, Springer US, pp. 223-278.

Popp, J., K. Pető, and J. Nagy. 2013. "Pesticide productivity and food security. A review." *Agronomy for Sustainable Development* 33:243-255.

Pu, J., Z. Wang, and H. Chung. 2020. "Climate change and the genetics of insecticide resistance." *Pest Management Science* 76:846-852.

Relyea, R.A. 2005. "The impact of insecticides and herbicides on the biodiversity and productivity of aquatic communities." *Ecological Applications* 15:618-627.

Roodman, D. 2009. "A Note on the Theme of Too Many Instruments*." *Oxford Bulletin of Economics and Statistics* 71:135-158.

Savary, S., L. Willocquet, S.J. Pethybridge, P. Esker, N. McRoberts, and A. Nelson. 2019. "The global burden of pathogens and pests on major food crops." *Nature Ecology & Evolution* 3:430-439.

Schaub, S., R. Huber, and R. Finger. 2020. "Tracking societal concerns on pesticides – a Google Trends analysis." *Environmental Research Letters* 15:084049.

Sharma, S., R. Kooner, and R. Arora (2017) "Insect Pests and Crop Losses." In R. Arora, and S. Sandhu eds. *Breeding Insect Resistant Crops for Sustainable Agriculture.* Singapore, Springer Singapore, pp. 45-66.

Skevas, T., A.O. Lansink, and S.E. Stefanou. 2012. "Measuring technical efficiency in the presence of pesticide spillovers and production uncertainty: The case of Dutch arable farms." *European Journal of Operational Research* 223:550-559.

Skevas, T., S.E. Stefanou, and A.O. Lansink. 2014. "Pesticide use, environmental spillovers and efficiency: A DEA risk-adjusted efficiency approach applied to Dutch arable farming." *European Journal of Operational Research* 237:658-664.

Stehle, S., and R. Schulz. 2015. "Agricultural insecticides threaten surface waters at the global scale." *Proceedings of the national Academy of Sciences* 112:5750.

Sydow, J., G. Schreyögg, and J. Koch. 2009. "Organizational Path Dependence: Opening the Black Box." *Academy of Management Review* 34:689-709.

Tang, F.H.M., M. Lenzen, A. McBratney, and F. Maggi. 2021. "Risk of pesticide pollution at the global scale." *Nature Geoscience* 14:206-210.

Tsionas, E.G., and S.C. Kumbhakar. 2014. "Firm Heterogeneity, Persistent and Transient Technical Inefficiency: A Generalized True Random-Effects Model." *Journal of Applied Econometrics* 29:110-132.

Varah, A., K. Ahodo, S.R. Coutts, H.L. Hicks, D. Comont, L. Crook, R. Hull, P. Neve, D.Z. Childs, R.P. Freckleton, and K. Norris. 2020. "The costs of human-induced evolution in an agricultural system." *Nature Sustainability* 3:63-71.

Vergne, J.-P., and R. Durand. 2010. "The Missing Link Between the Theory and Empirics of Path Dependence: Conceptual Clarification, Testability Issue, and Methodological Implications." *Journal of Management Studies* 47:736-759.

Way, M.J., and H.F. van Emden. 2000. "Integrated pest management in practice — pathways towards successful application." *Crop Protection* 19:81-103.

Weddle, P.W., S.C. Welter, and D. Thomson. 2009. "History of IPM in California pears—50 years of pesticide use and the transition to biologically intensive IPM." *Pest Management Science* 65:1287-1292.

Wilson, B.E. 2021. "Successful Integrated Pest Management Minimizes the Economic Impact of Diatraea saccharalis (Lepidoptera: Crambidae) on the Louisiana Sugarcane Industry." *Journal of Economic Entomology* 114:468-471.

Wilson, C., and C. Tisdell. 2001. "Why farmers continue to use pesticides despite environmental, health and sustainability costs." *Ecological Economics* 39:449-462.

Windmeijer, F. 2005. "A finite sample correction for the variance of linear efficient two-step GMM estimators." *Journal of econometrics* 126:25-51.

---. "A finite sample correction for the variance of linear two-step GMM estimators." Institute for Fiscal Studies.

Xu, R., R. Kuang, E. Pay, H. Dou, and G.R. de Snoo. 2008. "Factors contributing to overuse of pesticides in western China." *Environmental Sciences* 5:235-249.

Appendices

Appendix A: Log-likelihood using properties of the Closed-Skewed Normal distribution

Let $\alpha_i = a_i + c_i$ and $\eta_{it} = b_{it} + w_{it}$. Each of these composed error follow a skew normal distribution which pdf is well defined (Aigner et al., 1977, Azzalini, 2013, Meeusen and Vandenbroeck, 1977). Thus the composed error $\alpha_i + \eta_{it}$ follows a Closed-Skewed Normal distribution by being the sum of two independent skew normal distributions. In compact form, model (6) can be written as

$$\mathbf{z_i} = \lambda \mathbf{y_i} + \boldsymbol{\beta}'\mathbf{x_i} + \mathbf{1_{T_i}} a_i + \mathbf{b_i} + \mathbf{G}\mathbf{u_i} \tag{23}$$

where $\mathbf{u_i} = (c_i, w_{i1}, \dots, w_{iT_i})'$ and $\mathbf{b_i} = (b_{i1}, \dots, b_{iT_i})'$ are vectors of length $T_i + 1$ and T_i respectively, $\mathbf{G} = [\mathbf{1_{T_i}} \quad \mathbf{I_{T_i}}]$ is a matrix of dimension $T_i \times (T_i + 1)$, where $\mathbf{1_{T_i}}$ is the unity column vector of length T_i and $\mathbf{I_{T_i}}$ is the identity matrix of dimension T_i. $\boldsymbol{\epsilon}_\mathbf{i} = \mathbf{1_{T_i}} a_i + \mathbf{b_i} + \mathbf{G}\mathbf{u_i}$ follows a Closed-Skewed Normal distribution, and the joint distribution (accounting) for the panel dimension is given by[17]

$$\begin{aligned} &\log L_i(\lambda, \boldsymbol{\beta}, \sigma_a, \sigma_b, \sigma_c, \sigma_w) \\ &\qquad = (T_i + 1)\log 2 \\ &\qquad + \log \boldsymbol{\phi}_{T_i}(\mathbf{z_i} - \lambda \mathbf{y_i} - \boldsymbol{\beta}'\mathbf{x_i}, 0, \boldsymbol{\Sigma}_\mathbf{i} + \mathbf{G}\mathbf{V_i}\mathbf{G}') \\ &\qquad + \log \overline{\boldsymbol{\Phi}}_{T_i+1}(\mathbf{R_i}(\mathbf{z_i} - \lambda \mathbf{y_i} - \boldsymbol{\beta}'\mathbf{x_i}), \boldsymbol{\Lambda}_\mathbf{i}) \end{aligned} \tag{24}$$

Where $\boldsymbol{\Sigma}_\mathbf{i} = \sigma_b \mathbf{1_{T_i}} + \sigma_a \mathbf{1_{T_i}}\mathbf{1_{T_i}}'$, $\mathbf{V_i} = \begin{bmatrix} \sigma_c & \mathbf{0}'_{T_i} \\ \mathbf{0}_{T_i} & \sigma_w \mathbf{1_{T_i}} \end{bmatrix}$, $\boldsymbol{\Lambda}_\mathbf{i} = \left(\mathbf{V_i^{-1}} + \mathbf{A}'\boldsymbol{\Sigma}_\mathbf{i}^{-1}\,\mathbf{G}\right)^{-1}$, $\mathbf{R_i} = \boldsymbol{\Lambda}_\mathbf{i}\mathbf{G}'\boldsymbol{\Sigma}_\mathbf{i}^{-1}$, and $\boldsymbol{\phi}_q(\mathbf{s}, \boldsymbol{\mu}, \boldsymbol{\Omega})$ denotes the density at $\mathbf{s}$ of a q-variate normal distribution with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Omega}$ while $\overline{\boldsymbol{\Phi}}_{T_i+1}(\boldsymbol{\mu}, \boldsymbol{\Omega})$ is the joint probability that a q-variate normal distribution with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Omega}$ belongs to the nonnegative orthant.

[17] See Badunenko and Kumbhakar (2017), Badunenko and Kumbhakar (2016), Colombi et al. (2014).

Appendix B: Conditional efficiency using moment conditions of the Closed-Skewed Normal distribution

We have:

$$E[\exp(\mathbf{t}'\mathbf{u_i})\,|\boldsymbol{\epsilon}_\mathbf{i}] = \frac{\bar{\boldsymbol{\Phi}}_{T_i+1}(\mathbf{R_i}\boldsymbol{\epsilon}_\mathbf{i} + \ \boldsymbol{\Lambda}_\mathbf{i}\boldsymbol{t}, \boldsymbol{\Lambda}_\mathbf{i})}{\bar{\boldsymbol{\Phi}}_{T_i+1}(\mathbf{R_i}\boldsymbol{\epsilon}_\mathbf{i}, \boldsymbol{\Lambda}_\mathbf{i})}\exp[\mathbf{t}'\mathbf{R_i}\boldsymbol{\epsilon}_\mathbf{i} + \frac{1}{2}\mathbf{t}'\boldsymbol{\Lambda}\mathbf{t}] \qquad (25)$$

Where $\boldsymbol{\epsilon}_\mathbf{i} = \mathbf{z_i} - \lambda\mathbf{y_i} - \ \boldsymbol{\beta}'\mathbf{x_i}$, and

$$\mathbf{u_i} = \begin{bmatrix} a_i \\ w_{i1} \\ \vdots \\ w_{iT_i} \end{bmatrix}, \mathbf{t} = \begin{bmatrix} -1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ \vdots \\ 0 \end{bmatrix}, \cdots, \begin{bmatrix} 0 \\ 0 \\ \vdots \\ -1 \end{bmatrix}$$

The conditional efficiencies estimation involves multivariate normal integration which is done using the GHK simulator.

Appendix C: Summary Statistics of Extenso and pooled sample between 2009-2018

	Extenso farms		All farms (Intensive + Extenso)	
	Main Model variables			
Variables	Mean	St. Dev.	Mean	St. Dev.
Wheat production (dt) Y	261.4	216.9	338.8	281.2
Pesticides Load index (LI) Z	3.2	4.8	8.3	14.9
Active Ingredients (AI) Z	3.3	5.4	7.0	9.7
Treatment Frequency Index (TFI) Z	1.5	0.8	2.1	1.4
Nitrogen use (kilograms) X_1	648.9	589.7	808.9	725.3
Labor and machinery costs (constant CHF) X_2	4,533	3,516	6,042	4,906
Mechanical weeding (constant CHF) X_3	1,281	1,314	1,449	1,515
Wheat surface (hectares) X_4	4.5	3.7	5.5	4.3
Wheat price per dt (CHF)	47.0	5.9	46.4	6.2
Pesticides price (CHF/active ingredient)	2,250	2,808	3,372	25,683
	Other additional variables			
Wheat yield (tons/hectare)	5.8	-	-	-
Pesticides Load index per hectare	0.87	-	-	-
Active Ingredients per hectare	0.80	-	-	-
Nitrogen use (kilograms/hectare)	144	-	-	-
Labor and machinery costs per hectare	1038	-	-	-
Mechanical weeding per hectare	300	-	-	-
Wheat revenues (constant CHF/hectare)	2659	-	-	-
Number of observations	461		1,062	

Source: CE-AEI and authors' computations.
Note: Monetary values are expressed in December 2015 Swiss Francs (CHF)

Appendix D: Full results of GMM for Intensive wheat producers

Variables	LI	AI	TFI
Wheat Production (Y)	2.06	4.28	1.68^{*}
	(1.95)	(3.31)	(0.85)
Nitrogen (x_1)	0.27	0.38	0.08
	(0.42)	(0.44)	(0.18)
Labor and machinery costs (x_2)	0.43	0.60	0.89
	(1.12)	(1.47)	(0.62)
Mechanical weeding costs (x_3)	-0.77	-0.50	-0.22
	(0.50)	(0.54)	(0.36)
Production surface (x_4)	-1.75	-4.20	-2.49^{***}
	(1.86)	(2.97)	(0.80)
Year_2009	-11.60	-23.25^{*}	-12.79^{***}
	(8.80)	(11.75)	(4.11)
Year_2010	-11.70	-23.27^{*}	-12.80^{***}
	(8.83)	(11.74)	(4.08)
Year_2011	-11.83	-23.23^{*}	-12.83^{***}
	(8.83)	(11.77)	(4.07)
Year_2012	-11.85	-23.26^{*}	-12.78^{***}
	(8.84)	(11.67)	(4.08)
Year_2013	-12.10	-23.37^{*}	-12.88^{***}
	(8.80)	(11.70)	(4.06)

Variables	LI	AI	TFI
Year_2014	-12.15	-23.71*	-12.90***
	(8.75)	(11.66)	(4.05)
Year_2015	-12.52	-23.57*	-13.00***
	(8.63)	(11.57)	(4.00)
Year_2016	-12.26	-23.48*	-12.87***
	(8.57)	(11.36)	(3.99)
Year_2017	-12.45	-24.14*	-13.03***
	(8.76)	(11.63)	(4.05)
Year_2018	-12.43	-24.10*	-13.01***
	(8.72)	(11.63)	(4.01)
Sargan Statistic	30.44	29.87	30.45
Sargan test p-value	0.21	0.23	0.21

***p < 0.001; **p < 0.01; *p < 0.05

Note: lower-case letters y, x_1, x_2, x_4 represents logarithms of Y, X_1, X_2, X_4 respectively and x_3 is the IHS transformation of X_3. Parameters standard errors are in brackets.

Appendix E: Full results of GMM for Extenso farms and pooled sample

	Extenso			Pooled sample		
Variables	**LI**	**AI**	**TFI**	**LI**	**AI**	**TFI**
Wheat Production (Y)	-0.56	-0.81	-0.22	0.79	-0.74	0.46
	(0.98)	(1.27)	(0.38)	(1.21)	(1.18)	(0.42)
Nitrogen (x_1)	0.04	-0.51	-0.03	0.08	-0.25	-0.15
	(0.32)	(0.47)	(0.14)	(0.26)	(0.30)	(0.11)
Labor and machinery costs (x_2)	1.18	1.73	-0.16	1.39**	2.34***	0.69**
	(0.77)	(1.34)	(0.43)	(0.55)	(0.67)	(0.27)
Mechanical weeding costs (x_3)	-0.78*	-1.31*	0.07	-1.07***	-1.41***	-0.04
	(0.39)	(0.66)	(0.20)	(0.32)	(0.40)	(0.17)
Production surface (x_4)	0.10	0.78	0.26	-0.90	0.36	-0.96
	(1.17)	(1.54)	(0.66)	(1.46)	(1.39)	(0.60)
Year_2009	-5.77	-6.04	2.50	-12.88*	-12.00*	-5.39*
	(5.37)	(8.63)	(3.74)	(6.38)	(6.08)	(2.78)
Year_2010	-5.77	-5.96	2.59	-12.92*	-11.99*	-5.35*
	(5.39)	(8.61)	(3.74)	(6.36)	(6.11)	(2.77)
Year_2011	-5.77	-6.04	2.56	-13.03*	-11.99*	-5.37*
	(5.36)	(8.48)	(3.73)	(6.36)	(6.11)	(2.79)
Year_2012	-6.13	-6.54	2.45	-13.18*	-12.49*	-5.41*
	(5.36)	(8.55)	(3.74)	(6.33)	(6.03)	(2.76)

Variables	Extenso LI	Extenso AI	Extenso TFI	Pooled sample LI	Pooled sample AI	Pooled sample TFI
Year_2013	-5.91	-6.68	2.36	-13.10*	-12.25*	-5.42*
	(5.37)	(8.50)	(3.69)	(6.30)	(6.04)	(2.75)
Year_2014	-5.89	-6.38	2.43	-13.21*	-12.21*	-5.45*
	(5.43)	(8.45)	(3.75)	(6.39)	(6.14)	(2.77)
Year_2015	-6.10	-6.46	2.40	-13.46*	-12.39*	-5.56*
	(5.41)	(8.58)	(3.74)	(6.38)	(6.06)	(2.75)
Year_2016	-6.35	-7.37	2.48	-13.25*	-12.55*	-5.48*
	(5.31)	(8.66)	(3.71)	(6.26)	(5.98)	(2.72)
Year_2017	-5.83	-6.40	2.57	-13.25*	-12.45*	-5.49*
	(5.29)	(8.56)	(3.74)	(6.36)	(6.07)	(2.74)
Year_2018	-6.62	-6.71	2.40	-13.49*	-12.60*	-5.51*
	(5.29)	(8.44)	(3.71)	(6.36)	(6.09)	(2.73)
Sargan Statistic	25.90	27.08	40.12	43.67	46.72	50.88
Sargan test p-value	0.84	0.79	0.22	0.44	0.32	0.19

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

For the Extenso farms, the lag length is four and the lead three, while for the pooled sample, we retained five and four respectively for the lag and the lead.

Appendix F: Persistent and Transient Efficiency Model for Extenso and Pooled samples

	Extenso			Pooled sample		
	LI	*AI*	*TFI*	*LI*	*AI*	*TFI*
(Intercept)	-0.25	-0.02	0.02	-0.15	0.27	-0.04
	(0.23)	(0.25)	(0.08)	(0.25)	(0.22)	(0.09)
Kantonal dummies	Yes	Yes	Yes	Yes	Yes	Yes
$\ln\lambda = \ln\frac{\sigma_w}{\sigma_b}$	-4.76	-4.26	-4.70	-5.30	-5.10	-5.05
	(10.76)	(6.05)	(9.21)	(14.09)	(10.72)	(10.88)
$\ln\sigma = \ln\sqrt{\sigma_w^2 + \sigma_b^2}$	0.15^{***}	0.27^{***}	-0.85^{***}	0.22^{***}	0.29^{***}	-0.75^{***}
	(0.02)	(0.02)	(0.04)	(0.02)	(0.01)	(0.03)
$\ln\sigma_a^2$	-0.44^{***}	-0.50^{***}	-1.66^{***}	-0.24^{***}	-0.28^{***}	-1.26^{***}
	(0.12)	(0.13)	(0.28)	(0.07)	(0.07)	(0.12)
$\ln\sigma_c^2$	-29.74	-30.18	-26.56	**-1.10^{*}**	-28.35	**-1.73^{***}**
	NA	NA	NA	(0.49)	NA	(0.22)
Mean Persistent Efficiency	1.00	1.00	1.00	0.68	1.00	0.77
Mean Transient Efficiency	0.93	0.90	0.95	0.94	0.93	0.96
Mean Total Efficiency	0.93	0.90	0.95	0.64	0.93	0.73

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Appendix G: Share of Persistent Inefficiency distribution in Total Inefficiency for pooled sample

	LI	TFI
Min	0.76	0.80
1st Quartile	0.84	0.85
Median	0.86	0.86
Mean	0.86	0.86
3rd Quartile	0.87	0.87
Max	0.92	0.90