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Estimation and comparison of the performance of low-input and conventional agricultural production systems.

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Abstract

Sustainable intensification through low-input production systems can mitigate agriculture's environmental impact while meeting the food demands of a growing population. However, comparing the performance of low-input system to conventional one, particularly in terms of productivity and yield, is challenging due to selection bias. To effectively develop policies promoting the adoption of low-input system and assess their impact on pesticide use and yields, it is crucial to employ an econometric framework that addresses these issues. This article proposes an endogenous switching approach combined with control functions to tackle selection bias and input endogeneity simultaneously. Using unbalanced panel data on Swiss wheat production, which includes both low-input and conventional systems, our framework reveals significant disparities in input demands and production functions. These differences have implications for how farmers, their input demands, and yields respond to public policies targeting pesticide use.

Keywords: Low-input Production Systems, Primal Production Function, Endogenous Switching Regression, Control Function.

1 Introduction

The need for a more sustainable agriculture is pressing and the reduction of adverse environmental and health effects of agriculture is on top of the agenda of food-value chain actors in Europe and globally (Möhring, et al., 2020). The Farm to Fork strategy of the European Union and the Convention for Biological Diversity's Global Biodiversity Framework aim to largely reduce pesticide use and risk and fertilizer use (Möhring et al. 2023; Schebesta & Candel 2020). While current agricultural practices often have deleterious effect on the environment and on biodiversity, there is a need to maintain high production levels for food security (Foley et al. 2005, 2011). Low-input production systems have been proposed as a compromise between environmental and food production concerns as they are scalable and thus applicable for large shares of production practices (Aune 2012; Fess et al. 2011; Maitra et al. 2021; Meynard 2008). They are characterized by the use of adjusted management, e.g., using agronomic principles and new technologies (e.g., new varieties) that substantially reduce the use of synthetic pesticides and/or mineral fertilizers (Bertrand & Doré 2008; Meynard & Girardin 1991; Rolland et al. 2003). A key question is the comparison of low-input and conventional production systems, e.g., in terms of yield and productivity. This also has implications for the efficiency of policies such as input taxes in low-input vis-à-vis conventional production systems. However, this comparison is often hampered by methodological challenges, e.g., due to selection biases.

This paper seeks to estimate and compare the production function of low-input production systems regarding conventional, high-input production systems. We propose an endogenous switching approach to test and control for production system selection bias. More specifically, this article considers a non-linear framework while allowing the selection bias to impact the response variable (e.g., farmer's yield) as well as the endogenous covariates (e.g., the variable inputs). The resulting production technology is described both by a production function and input demand equations that are specific to the considered production system. We illustrate the approach using Swiss wheat production, where both conventional high-input and a low-input wheat production practices exist in parallel. More precisely, our empirical analysis uses unbalanced panel data containing detailed information on output and input use obtained from field journals (de Baan et al. 2020; Gilgen et al. 2023). Arable crops and especially cereals represent a large part of the European agricultural crop area and are crucial to reach food security objectives. We here focus especially on wheat that represents half of grown cereals and thus represents a significant share of European pesticide use in European agriculture. The here developed approach aims to help designing efficient policies for the uptake of these extensive production systems while evaluating the impact on pesticide use and yields. Consequently, we choose to use a primal approach of the production function to be able to quantify the relation between input uses and output in low-input and conventional production systems.

Whilst organic production system has been widely compared to the conventional one in the literature (Acs et al. 2007; Gardebroeck et al. 2010; Lansink et al. 2002; Serra et al. 2008; Seufert et al. 2012), studies considering low-input production system more generally are

limited. Earlier research on low-input production systems was especially focussed on agronomic aspects (Dawson et al. 2008; Kong et al. 2011; Loyce et al. 2008; Schrama et al. 2018) or on the determinants of (non-) adoption (Finger & El Benni 2013; Ricome et al. 2016; Vanloqueren & Baret 2008). Femenia and Letort (2016) is a notable exception as they rely on two production functions - a conventional and a low-input one - to evaluate the impact of a pesticide tax. Yet, they rely on experimental agronomic data on low-input production system to estimate the changes from the conventional production technology. Most data sets used by agricultural production economists do not contain relevant information to distinguish low-input production system from conventional ones.

When available, a key methodological challenge using observational – instead of experimental – data is selection biases. For example, Finger and El Benni (2013), low-input adopters of low-input production system tend to be “smaller” farmers with already “lower” yields, which may indicate that opportunity costs of adopting low-input production system are lower for smaller farms. Additionally, the choice to adopt practices with more uncertain pay-offs might reflect differences in farmers' behavior. Mzoughi (2011) shows that farmers adopting integrated crop protection tend to value social (here environmental) concern. Such factors, that are affecting both technology choice and other production choices and outcomes, if unobserved, induce endogeneity issues (that are known in this case as selection bias).¹ Such self-selection effects and selection biases are well-known when dealing with technology choice. Endogenous regime switching models are standard in production choice models to account for such selection biases (Abdulai & Huffman 2014; Alene & Manyong 2007; Asfaw et al. 2012).

In addition to selection biases, agricultural production functions generally suffer from input endogeneity issues (Marschak & Andrews 1944). Especially primal production functions as they make explicit the relationship between output (e.g., yield) and inputs (e.g., pesticides). Yet, most drivers of inputs use choice are unobserved to the analyst and might also affect the observed yield. Whilst applied economists have devoted much attention to this endogeneity problem and approaches to solve it (Ackerberg et al. 2015), there are only few studies that consider endogenous covariates within a endogenous switching framework (Murtazashvili & Wooldridge 2016; Takeshima & Winter-Nelson 2012). If they allow for correlation between the selection term and the endogenous covariates, none of these studies consider that the selection bias can affect both the endogenous covariates and the response function. Yet, when considering production system choice, it is unlikely to consider that such choice affects observed yield without impacting farmer's input choice as well.

We aim to fill this gap by estimating the production function of low-input wheat production system and compare it to the conventional one. We consider an endogenous switching approach to test for production system selection bias on the yield and input use levels. In particular, we use a control function approach to account for input endogeneity endogeneity

¹ Many common factors are impacting both production system choice on the one hand, and production choices and outcomes on the other hand. If many of these factors are observed (e.g. market prices, weather conditions or general farmer characteristics), many of them are unobserved -- including soil quality, farmer skills or their environmental preferences.

(Akerberg et al. 2015; Marschak & Andrews 1944) and a corrected inverse Mills ratio to account for the production system selection bias on the input demand equation. We find that, whilst this selection bias does not directly affect Swiss farmers' production function, it does affect their input demand and thus, indirectly, their yield. This result speaks in favor of accounting for selection bias not only on farmers' production function but also on their input demand.

Our framework also allows us to investigate how farmer's input demand reacts to price variations. Because variable inputs are used more parcimoniously in low-input production system, one can assume that they respond less to price variation. On the other hand, conventional production system allows for quantity adjustment when the relative price of input increases. Deriving from that is the fact that pesticides – especially if targeting herbicides – taxation policies could have a negative impact on low-input production systems. Low-input herbicide demand being rather inelastic, an increase in herbicide cost would result in a decrease profitability for those farmers. Conventional farmers, as they benefit from adjustment margins in their input uses, could more easily absorb the induced cost increase.

Finally, our examination of the production functions shows that the role inputs are playing in production – e.g., productive or damage abating – can be different across production systems. More generally, we find that the role of production conditions, such as temperature and rainfall levels, might differ between conventional and low-input yields. This needs to be accounted for when estimating the low-input and conventional production functions and evaluating the potential yield impact of policies that might affect pesticide use levels (e.g., a glyphosate ban).

Overall, our results advocate for considering separately low-input and conventional producers when implementing pesticide reduction policies.

The remainder of this article is structured as follows. The next section is dedicated to the presentation of our endogenous regime switching framework with selection on both the output and inputs. Following is the section where we present the Swiss observational data we consider for our empirical application. Then, we describe and compare the Swiss low-input and conventional production systems for wheat. Finally, results will be discussed so we can draw conclusions from this work.

2 An endogenous regime switching model with endogenous covariates and double selection process

2.1. From an endogenous switching regime model

Most studies comparing conventional with alternative production systems - in terms of productivity, production risk or efficiency - consider separate functions thereby considering that they represent different technologies (Gardebreek 2006; Gardebreek et al. 2010; Lansink et al. 2002). Similarly, low-input farming systems may be considered separately from conventional farming systems when estimating production functions. Indeed, low-input farming systems were conceived by agronomist to allow for chemical input, e.g. pesticides and mineral fertilizers, reduction (Meynard 1985; Rolland et al. 2003). To substitute chemical

inputs, farmers adopting low-input production system can benefit from integrated production practices (e.g., soil preparation operations, beneficial management practices or crop rotations) but also from innovation such as crop breeding (Fess et al. 2011; Möhring, Ingold, et al. 2020; Rolland et al. 2003). Instead of being at the core of crop protection, pesticides are one element among others that should only be used when there is no other option left in integrated production (Lucas 2007). Consequently, we have two equations corresponding to the production technology of low-input farming systems (denoted as regime $r = 1$) and the production technology of conventional ones ($r = 0$):

$$(1) \begin{cases} \ln(y^0) = \ln f^0(\mathbf{x}, \mathbf{c}; \boldsymbol{\beta}^0) + v^0 \\ \ln(y^1) = \ln f^1(\mathbf{x}, \mathbf{c}; \boldsymbol{\beta}^1) + v^1 \end{cases}$$

where y^r correspond to observed yield in regimen r , f^r are farming system specific production functions, \mathbf{x} the vector of input use levels and \mathbf{c} the vector of control variables that might impact production choices (e.g., topographic and weather conditions). Finally, terms $\boldsymbol{\beta}^r$ and v^r represent respectively the vector of parameters and the error term of the yield model.

If the underlying agronomic principles of low-input and conventional farming systems ask for separate production function, our economic modelling should also account for the potential endogenous selection issues in the farming system choice. As aforementioned, farmers might face heterogenous opportunity costs and different utility functions that affect both their decision to adopt low-input farming system and their production function (Finger & El Benni 2013; Mzoughi 2011). If such selection bias is not accounted for when estimating the low-input and conventional production technology, it will lead to biased estimates. The most adopted strategy to account for such bias in the agricultural production literature are endogenous regime switching models (Lee 1982). This approach was adopted for instance by Alene and Manyong (2007) to evaluate the impact of farmer education on the productivity with traditional and improved technology. Endogenous regime switching model were also used by Asfaw et al. (2012) and Abdulai and Huffman (2014). In line with these previous studies, we consider in this article an endogenous regime switching model. To define such model, we need to define a selection equation for farming system choice in addition to Equation (1). Let consider a standard linear index model:

$$(2) \begin{cases} r^* = \gamma_0 + \boldsymbol{\gamma}_z \mathbf{z} + e \\ r = 1\{r^* \geq 0\} \end{cases}$$

where r^* is the latent variable for farming system choice and r its observable counterpart. $(\gamma_0, \boldsymbol{\gamma}_z)$ and e respectively correspond to the vector of parameters and the error term of this dichotomous choice model and \mathbf{z} is used as a vector of instrument variables for endogenous farming system choice r . Among those instrument variables are the set of control variables \mathbf{c} and variables that are expected to affect the farming system choice without directly impacting the yield (e.g., age, education).

In presence of self-selection effects, or more generally selection bias, the covariance between the error terms v^r and e is non-zero. It implies that the expected values of error terms v^r

conditional on r are different from zero and that our estimates of β^r are biased. To test and correct for this potential selection bias, the endogenous regime switching model relies on Heckman's approach (1979). In particular, Lee's (1982) extension of the Heckman selection correction approach gives us that:

$$(3) \quad \begin{cases} E[v^0 | \mathbf{z}, r = 0] = \omega_{ve}^0 \frac{-\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{1 - \Phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})} \\ E[v^1 | \mathbf{z}, r = 1] = \omega_{ve}^0 \frac{\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{\Phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})} \end{cases}$$

where ω_{ve}^r corresponds to the covariance between error terms v^r and e , φ and Φ respectively denote the probability and cumulative distribution function of the standard normal distribution.² Terms $\frac{\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{\Phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}$ and $\frac{-\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{1 - \Phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}$ correspond to the inverse Mills ratios and are integrated as a covariate in Equation (1) to control for selection bias. If estimates of ω_{ve}^r are significantly different from zero it indicates that selection bias is significant in our model.

2.2. To an endogenous switching regime with endogenous covariate model

Apart from the potential selection bias, our model as defined in Equation (1) might suffer from another estimation problem due to the input endogeneity issue, a long standing issue that has received much attention in the econometric literature (Ackerberg et al. 2015). Thus, we need to consider an "extended" endogenous regime switching model to the case of endogenous covariates (Murtazashvili & Wooldridge 2016; Takeshima & Winter-Nelson 2012). Takeshima and Winter-Nelson (2012) consider an approach combining an heteroskedastic probit to calculate the inverse Mills ratio coupled to a two-stage least square (2SLS) approach to estimate the model for the response variable and the endogenous covariate. On the other hand, Murtazashvili and Wooldridge (2016) consider a control function approach to control for the endogenous continuous covariates and a corrected inverse Mills ratio to allow for correlation between the discrete and continuous endogenous covariates. The approach we adopt in this article is similar to the one of Murtazashvili and Wooldridge (2016) but (i) considering a non-linear framework and (ii) assuming that the endogenous switching not only affect the response variable but also our endogenous covariates. The resulting model could be considered as an endogenous regime switching model with endogenous covariates and double selection process.

Let first define farming system specific input demand functions yield model as:

$$(4) \quad \begin{cases} \ln(x_k^0) = \alpha_{k,p}^0 \mathbf{p} + \alpha_{k,c}^0 \mathbf{c} + u_k^0 \\ \ln(x_k^1) = \alpha_{k,p}^1 \mathbf{p} + \alpha_{k,c}^1 \mathbf{c} + u_k^1 \end{cases}$$

² Heckman's selection correction relies on the assumption that $(v^r, e) | \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \Omega^r)$ with $\Omega^r = \begin{pmatrix} \omega_{vv}^r & \omega_{ve}^r \\ \omega_{ve}^r & 1 \end{pmatrix}$. Despite being standard, the normalization restriction stating that $Var(e) = 1$ can be problematic in our case as farmers are generally observed for several years. This point is further examined in the Discussion section.

where k corresponds to the index of the variable input considered, \mathbf{p} represents the vector of relevant prices (e.g., crop and input prices), $(\boldsymbol{\alpha}_{k,p}^r, \boldsymbol{\alpha}_{k,c}^r)$ are the vector of parameters and u_k^r is the error term. Input endogeneity implies that the covariances between error terms e_k^r and ε^r are non-zero and that our estimates of $\boldsymbol{\beta}^r$ in Equation (1) are still biased. To correct for such bias, we consider a control variable approach (Wooldridge 2015). Assuming that there is only one input k that is endogenous and putting aside the selection bias, we can define the control function as:

$$(5) \quad \begin{cases} E[\varepsilon^0 | \mathbf{x}] = \rho_{vu}^0 u_k^0 \\ E[\varepsilon^1 | \mathbf{x}] = \rho_{vu}^1 u_k^1 \end{cases}$$

where terms ρ_{vu}^r are to be estimated and represents the intensity of the correlation between error terms v^r and u_k^r .³

The selection bias and input endogeneity corrections presented respectively in Equation (3) and (5) might be additive assuming that error terms e_k^r and μ are uncorrelated. Yet, one can reasonably assume that the unobserved factor that are affecting both the farming system choice and the observed yield are also affecting the input demand. In that case, it means that corrections (3) and (5) are not additive and that estimates of $(\boldsymbol{\alpha}_{k,p}^r, \boldsymbol{\alpha}_{k,c}^r)$ are biased due to uncorrected selection bias. As for Equation (1), we consider a Heckman selection correction for the input demand equations:

$$(6) \quad \begin{cases} E[u_k^0 | \mathbf{z}, r = 0] = \omega_{k,ue}^0 \frac{-\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{1 - \phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})} \\ E[u_k^1 | \mathbf{z}, r = 1] = \omega_{k,ue}^0 \frac{\varphi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})}{\phi(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})} \end{cases}$$

where $\omega_{k,ue}^0$ corresponds to the covariance between error terms u_k^r and e . The error term of the input demand functions u_k^r can be decomposed in two parts: the selection correction part as presented in Equation (7) and a random part η_k^r . Thus, setting aside the selection bias, the control function as presented in Equation (5) can be rewritten as:

$$(7) \quad \begin{cases} E[v^0 | \mathbf{x}] = \rho_{vu}^0 [\omega_{k,ue}^0 \lambda^r(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z}) + \eta_k^0] = \rho_{vu}^0 u_k^0 \\ E[v^1 | \mathbf{x}] = \rho_{vu}^1 [\omega_{k,ue}^1 \lambda^r(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z}) + \eta_k^1] = \rho_{vu}^1 u_k^1 \end{cases}$$

where $\lambda^r(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})$ represents the inverse Mills ratio and ρ_{vu}^r represents the intensity of the correlation between error terms v^r and u_k^r .

Last step so we can write $E[v^0 | \mathbf{x}, \mathbf{z}, r = 0]$ and $E[v^1 | \mathbf{x}, \mathbf{z}, r = 1]$ is to correct for the existing correlation between the selection correction of Equation (3) and the control function

³ We are only assuming that there is one endogenous input to simplify the notation. We can easily extend the approach to the case of multiple endogenous inputs. Instead of the vector u_k^r and the scalar ρ_{vu}^r we have a matrix \mathbf{u}^r and a vector $(\boldsymbol{\rho}_{vu}^r)'$ with respectively as much columns, as much elements, as the number of endogenous inputs.

presented in Equation (8). Indeed, the inverse Mills ratio is part of the control function. To account for such correlation, we consider a corrected version of the inverse Mills ratio:⁴

$$(8) \lambda_y^r = (\psi_{ee}^r)^{-\frac{1}{2}} \lambda^r \left((\psi_{ee}^r)^{-\frac{1}{2}} (\gamma_0 + \boldsymbol{\gamma}'_z \mathbf{z} + \rho_{eu}^r u_k^r) \right)$$

where ρ_{eu}^r represents the covariance between error terms u_k^r and e and $\psi_{\mu\mu}^r$ is a scale parameter.⁵ Finally, combining Equations (7) and (8) we have:

$$(9) \begin{aligned} E[v^0 | \mathbf{x}, \mathbf{z}, r = 0] &= \psi_{ve}^0 \lambda_y^0 + \rho_{vu}^0 u_k^0 \\ E[v^1 | \mathbf{x}, \mathbf{z}, r = 1] &= \psi_{ve}^1 \lambda_y^1 + \rho_{vu}^1 u_k^1 \end{aligned}$$

2.3. A Cobb-Douglas crop production function with a damage abatement part

In this part, when not necessary we omit the farming system specific index r to simplify notations. To represent the damage abating role of pesticides in the production process compared with the "productive" inputs we consider a damage abatement function as proposed by Lichtenberg and Zilberman (1986). Hence, the production function $f(\mathbf{x}, \mathbf{c}; \boldsymbol{\beta})$ is separated in two parts: a potential yield function (noted $h(\cdot)$) and a damage abating function (noted $d(\cdot)$). The potential yield function describes how productive inputs contribute to the maximum potential crop yield level, i.e., the yield level that is free of any damage due to weeds, pests and/or diseases. On the other hand, the damage abating function gives the share of potential yield that is saved by using pesticides: $d(\cdot)$ range is positive and should not exceed 1. Besides, to account for the potential complementary of inputs between them we allow inputs to have both a productive and damage abating role on crop yields (Saha et al. 1997). Thus, we have three different set of inputs: the purely productive inputs (noted $\mathbf{x}_{(h)}$), the purely damage abating inputs (noted $\mathbf{x}_{(i)}$) and the interactive inputs (noted $\mathbf{x}_{(d)}$). As low-input and conventional farming system rely on different agronomic principles, we allow the sets of purely productive, purely damage abating and interactive inputs to differ across production technologies.

Following Zhengfei et al. (2005, 2006) and Möhring, Bozzola et al. (2020), our empirical crop yield function models combine Cobb-Douglas potential yield functions:

$$(10) h(\mathbf{x}_{(h)}, \mathbf{x}_{(i)}, \mathbf{c}; \boldsymbol{\beta}) = \exp(\boldsymbol{\beta}_{(c)} \mathbf{c}) \cdot \exp(\ln \mathbf{x}_{(h)} \boldsymbol{\beta}_{(h)} + \ln \mathbf{x}_{(i)} \boldsymbol{\beta}_{(i)})$$

where $\exp(\boldsymbol{\beta}_{(c)} \mathbf{c})$ represents the impact of production conditions and farms' characteristics on crop yields; and quadratic damage abatement functions:

$$(11) d(\mathbf{x}_{(d)}, \mathbf{x}_{(i)}; \boldsymbol{\gamma}) = \exp(-(\mathbf{B}_0 + \mathbf{B}_{(d)} \mathbf{x}_{(d)} + \mathbf{B}_{(i)} \mathbf{x}_{(i)})^2)$$

⁴ The corresponding assumption for Heckman's selection correction is that $(u_k^r, v^r, e) | \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \Omega^r)$ with

$$\Omega^r = \begin{pmatrix} \omega_{uu}^r & \omega_{uv}^r & \omega_{ue}^r \\ \omega_{uv}^r & \omega_{vv}^r & \omega_{ve}^r \\ \omega_{ue}^r & \omega_{ve}^r & 1 \end{pmatrix}.$$

⁵ The proof of result for the general case with multiple endogenous inputs is to be found in Chapter 1 of Devilliers (2021).

with $f(\mathbf{x}, \mathbf{c}; \boldsymbol{\beta}) = h(\mathbf{x}_{(h)}, \mathbf{x}_{(i)}, \mathbf{c}; \boldsymbol{\beta}) \cdot d(\mathbf{x}_{(d)}, \mathbf{x}_{(i)}; \mathbf{B})$. In particular, the quadratic damage abating function is convenient because it ensures $d(\cdot)$ range to be contained between 0 and 1 without imposing estimation restrictions on the signs of \mathbf{B} parameters. We can thus rewrite the farming system specific yield function from Equation (1) as:

$$(12) \ln(y^r) = \boldsymbol{\beta}_{(c)}^r \mathbf{c} + \ln \mathbf{x}_{(h)}^r \boldsymbol{\beta}_{(h)}^r + \ln \mathbf{x}_{(i)}^r \boldsymbol{\beta}_{(i)}^r - (\mathbf{B}_0^r + \mathbf{B}_{(d)}^r \mathbf{x}_{(d)}^r + \mathbf{B}_{(i)}^r \mathbf{x}_{(i)}^r)^2 + v^r$$

with the following decomposition for the error term:

$$(13) v^r = \psi_{ve}^r \lambda_y^r + \rho_{vu}^r u_k^r + \mu^r$$

where $\psi_{ve}^r \lambda_y^r$ and $\rho_{vu}^r u_k^r$ represent respectively the correction for selection bias and input endogeneity, and μ^r represents the random part of the error term.

2.4. Estimation strategy

The estimation approach we consider can be seen as an extension of Heckman's two-step approach for estimating standard endogenous switching regime models to the case with endogenous regressors (Heckman et al. 2003; Wooldridge 2010, 2015). In particular, our modeling framework relies on two sets of control functions: one to deal with the input use endogeneity issue and the other to deal with the sample selection issues.

First, we estimate the probit model for farming system choice - Equation (2) - by maximum likelihood. Estimates of $(\gamma_0, \boldsymbol{\gamma}_z)$ are used to estimate the inverse Mills ratio $\lambda^r(\gamma_0 + \boldsymbol{\gamma}_z \mathbf{z})$. Then, we can estimate by least squares the input demand functions - Equation (4) - augmented by the inverse Mills ratio to control for potential selection bias. Essentially, input demand functions are estimated following the standard Heckman two-step procedure. As for the yield function, we can easily estimate the u_k^r terms with the estimates of $(\boldsymbol{\alpha}_{k,p}^r, \boldsymbol{\alpha}_{k,c}^r)$ obtained at step 2. The problem comes when considering the estimation for the corrected Mills ratio λ_y^r . Equation (8) gives us that:

$$\lambda_y^r = (\psi_{ee}^r)^{-\frac{1}{2}} \lambda^r \left((\psi_{ee}^r)^{-\frac{1}{2}} (\gamma_0 + \boldsymbol{\gamma}_z' \mathbf{z} + \rho_{eu}^r u_k^r) \right).$$

We already have estimates for $(\gamma_0, \boldsymbol{\gamma}_z)$ and for u_k^r . We thus need to get estimates for ρ_{eu}^r and ψ_{ee}^r . Devilliers (2021) shows that both terms can be estimated using moment conditions.⁶ Once we have estimated the corrected inverse Mills ratio λ_y^r , the yield function given in Equation (12) can be estimated with non-linear least square.

In practice, each estimation step is fairly easy to implement. Yet, computing the asymptotic distribution of the estimators obtained by using the considered multiple step estimation procedure is not straightforward. Bootstrap methods were used so to get the empirical

⁶ In the case where we only have one endogenous input, ρ_{eu}^r corresponds to the empirical counterpart of the covariance between error terms u_k^r and e .

standard errors of the obtained estimates for the input demand and yield production functions (Efron & Tibshirani 1986; Fess et al. 2011).

3 Data

To investigate into the production technology of low-input farming systems compared to the conventional one, we consider Swiss data obtained from Agroscope, the Swiss center of excellence for agricultural research and provided by the Swiss Central Evaluation of Agri-Environmental Indicators (de Baan et al. 2020; Gilgen et al. 2023). Switzerland benefits from a voluntary integrated production program since 1992 (El Benni & Finger 2013). Farmer participation in the program is incentivized with a price mark-up of around 5 CHF/100kg (reflecting a ca. 10% price mark-up) and federal, per hectare direct payments of 400 CHF (Mack et al. 2023; Möhring & Finger 2022). These payments are conditional on farmers not using any fungicides, insecticides, plant growth regulators or chemical-synthetic stimulators of natural resistance.⁷ Among eligible crops - cereals, sunflower, rapeseed peas and beans - we focus on winter wheat production. This low-input “Extenso” wheat production currently represents more than 50% of the total Swiss wheat production (Finger & El Benni 2013).

Our dataset contains information on each management operation performed by the farmer – soil preparation, sowing, fertilization, crop protection operations and harvest, from 2009 to 2015. Following Möhring et al. (2020), we transform initial data consisting of daily records on crop management and inputs use as follows: we (i) calculate cost-equivalents for used machinery and working time, (ii) convert fertilizer applications into nitrogen equivalents and (iii) express pesticide use in terms of pesticide load. To this end, we use the Pesticide Load Index as implemented by Möhring et al. (2021) which accounts for differences in standard dosages and the heterogeneous properties of pesticides (Kudsk et al. 2018; Möhring et al. 2019). We combine this first dataset with farm-level bookkeeping data⁸ to obtain information on whether the farmer is participating in the Extenso production system for winter wheat (based on direct payments they receive).

The data is gathering 575 observations from 148 winter wheat farmers from 2009 to 2015. Among those farmers, 107 (resp. 60) experimented low-input (resp. conventional) practices representing 381 (resp. 194) observations. Switches between low-input and conventional farming systems are only concerning 19 farmers. Among those 19 farmers, 8 switched from conventional to low-input farming, 5 from low-input to conventional farming and 6 switched more than one time.⁹ Altogether, farmers were observed on average 3.56 (resp. 3.23) years in

⁷ In this low input scheme, fungicide and growth regulator use is substituted by variety choice and adjustment in farming practices. For weed control, both herbicides and mechanical weed control can be used. Note that the use of mineral fertilizer is not restricted in the low-input scheme.

⁸ This data is from retrieved Agroscope (Mouron & Schmid, 2012).

⁹ Among the farmers who switched more than once, we have the same number of farmers who switch from low-input to conventional first than the opposite.

the low-input subsample. Apart from switches and data collection, missing years for farmers could come from (i) crop rotation as we only consider winter wheat production, (ii) stopping winter wheat production, (iii) end of farming activity. In the absence of further information and given that farmer average number of years of observation is similar in the low-input and conventional subsamples, we consider those missing values to be randomly distributed and not affecting our estimators.

Table 1 provides crop specific and more general characteristics of high- and low-input farmers. In addition to standard descriptive statistics, we performed (i) Wilcoxon non-parametric test for the equality of mean of continuous variables and (ii) chi-squared contingency table test for categorical variables. As expected, for winter wheat cropping characteristics, farmers using low-input production system are using fewer chemical inputs and are facing lower yields than farmers using conventional production system.¹⁰ Yet, when looking at their economic return, we can see that despite their yield loss, their revenues per hectare are higher. If we remove the 400CHF/ha direct payment, low-input producers tend to have similar revenues from their conventional counterpart despite lower yield level. This can be explained by (i) the cost reduction associated to pesticide and work and machinery less intensive use and (ii) the wheat price premium they are benefiting from.

Apart from farmers' inputs uses and output, we also look at general characteristics of farms that can affect both their input uses and yield levels as well as the type of production practices farmers will adopt. First, low-input farmers tend to have smaller farms and a smaller area dedicated to winter wheat cropping. Second, farms located in mountaineous region are more represented among low-input farms. Yet, the average altitude of conventional farmers is not significantly different from the one of low-input farmers. Cantons were also considered to try to control for (i) heterogenous soil characteristics and (ii) potential differences in extension services (see Online Appendix B for cantonal repartition). We also introduced weather variables obtained for MeteoSwiss as to control for the variability of observed yield in the time that are due to environmental conditions (Frei 2014; Frei et al. 2006). We can see that weather conditions - average annual temperatures in °C and average annual rainfall in 1000 liter m⁻² - are comparable between the two subsamples.

Table 1: Descriptive statistics for conventional and low-input Swiss wheat farmers

	Conventional farmers	Low-input farmers	Mean-test
	Mean (sd)	Mean (sd)	p-value
Yield (t/ha)	65.41 (10.90)	58.50 (8.88)	***
Nitrogen (kg/ha)	151.81	141.78	***

¹⁰ Table 1 also shows that the use of insecticides is very limited, even among farmers using conventional production system. In the rest of this article, we only consider herbicide and fungicide uses.

	(51.59)	(48.10)	
Herbicide (LI/ha)	0.91	0.86	**
	(1.20)	(1.99)	
Fungicide (LI/ha)	1.70	0.04	***
	(1.22)	(0.22)	
Insecticide (LI/ha)	0.11	0.00	***
	(0.70)	(0.02)	
Mechanical pest control (CHF/ha)	315	315	0.91
	(179)	(209)	
Work & Machinery (CHF/ha)	1,434	1,115	***
	(261)	(243)	
Revenue (CHF/ha)	2,941	3,361	***
	(643)	(666)	
<hr/>			
Farm size (ha)	30.54	26.16	***
	(13.14)	(11.43)	
Share of winter wheat surface	20.10%	17.89%	***
	(10.55)	(10.07)	
<hr/>			
Mountain region	23.20%	34.91%	***
Altitude (m)	591	586	0.27
	(112)	(136)	
Temperatures (°C)	9.23	9.26	0.28
	(0.85)	(1.04)	
Log(Rainfall) (log(1000Lm ⁻²))	6.96	6.96	0.75
	(0.18)	(0.20)	
<hr/>			
Non-agricultural revenue (CHF)	25,215	33,937	***
	(43,195)	(33,038)	
Share of non-agricultural revenue	30.67 %	42.91 %	***
	(27.31)	(30.65)	
Share of rented land	43.24%	41.09%	0.87
	(31.77)	(28.36)	
Age of farm head	48.95	47.83	0.28
	(8.87)	(8.88)	
Education [†]	3.56	3.71	***
	(0.57)	(0.81)	
Labour intensity	0.059	0.063	0.33
	(0.025)	(0.030)	
<hr/>			
N	194	381	

Notes: * p<.1, ** p<.05, *** p<.01; LI = Load Index.

+ Education is a score variable from 1, no agricultural education, to 5, technical schooling. An increase in education score denotes a more educated farmer.

Based on the previous work of Finger and Lehmann (2012), we investigate other farm/farmer characteristics that could specifically impact the choice of production practices' type. Farmers with low-input production system tend to have a greater revenue coming from non-agricultural activities, in absolute and relative terms.¹¹ Also, farmers adopting low-input farming systems tend to be more educated than the one with conventional production system. For the other expected determinants of production practices' type choice - age of farm head, share of rented land and labour intensity - the observed difference between the high- and low-input farmers is not statistically significant. Yet, this descriptive analysis on the subsamples' characteristics is to be completed later with the analysis from the probit model results.

We also consider price variables to estimate the models for the choice of production practices' type and input uses. As for input prices, we consider the national representative price index (in CHF 2015) from Agristat (2015). Winter wheat prices, also from Agristat, can differ depending on (i) the chosen variety and (ii) the adoption of the Extenso production system. Extenso farmers benefit from a price premium that is around 5CHF/100kg. We keep the different variety prices to control for wheat quality, but the price premium is not accounted for as it is a consequence of the choice of production practices, not an explanatory factor. As winter wheat prices (and input prices to a lesser extent) are not observed by farmers when choosing technology and input uses, we should consider price anticipations. The most naïve anticipation is to use the observed prices at time $t - 1$. By doing so, we would have lost more than 10% of our sample as 2009 is the year when we have most observations. Steadiness of prices over the period encouraged us to use current year price as price anticipation.

A recapitulative table of the considered variables, their data source, and their role in our endogenous switching regime framework is provided in Online Appendix A.

4 Results and Discussion

4.1. The choice of production system and their specific variable input demand functions

Estimated predicted probability of choosing low-input production system is presented in Table 2. The negative impact of farm size and of the share of arable surface allocated to winter wheat cropping from our descriptive analysis is confirmed by our Probit model. An increase of one percentage point of the share of winter wheat reduces by 50% the probability to adopt a low-input production system among our sample. We also find that being in a mountaineous region increase by almost 15% the probability to adopt low-input farming systems production practices. It confirms the findings of Finger and El Benni (2013) on free-rider effects of the program for farms with a lower yield potential. Also, rainy years and/or

¹¹ We only keep the share of non-agricultural income as a potential instrument for the production system choice. Keeping both the value of non-agricultural income and its share could lead to endogeneity issues as we would get a proxy for the agricultural income, which likely depends on the choice of production practices.

being in rainier areas seem to be decrease the probabilty to adopt of low-input production system.

As for the variables we consider as specific determinants of the production system choice, our model shows that adoption of low-input production system tends to be favored by younger and more educated farmers. Also, a greater labour intensity and a greater share of revenue coming from non-agricultural activites increase the probability to adopt such production system. As for prices, input prices seem to have no significant impact on such choice. However, wheat price seems to have a quadratic - but no linear - effect on low-input production system adoption. Higher wheat prices are discouraging adoption at first but at a decreasing rate. Thus, it confirms at least partially the economic principle underlying the adoption og low-input production systemw. Low-input farming systems were designed to reduce the production costs in a context where support was increasingly decoupled. Hence, when crop prices are low, the incentive to reduce input costs is more important. On the contrary, high crop prices enact as an incentive to maximize yields, i.e., using conventional production system, for farmers.

Table 2: Estimated predicted probability of choosing low-input production system

	Conditional probability of adopting low-input production system	
Farm size	-0.003	*
	(0.002)	
Share of winter wheat surface	-0.500	**
	(0.215)	
Mountain	0.147	***
	(0.052)	
Altitude	0.000	
	(0.000)	
Temperatures	-0.031	
	(0.046)	
Log(Rainfall)	-0.307	*
	(0.164)	
Share of non-agricultural income	0.002	***
	(0.001)	
Share of rented land	0.000	
	(0.001)	
Age of farm head	-0.005	**
	(0.002)	
Education	0.135	***

	(0.027)
Labour intensity	1.537 *
	(0.807)
Wheat price ^a	0.057
	(0.044)
(Wheat price) ²	0.002 *
	(0.001)
Herbicide Price Index Ratio	1.820
	(4.449)
Fungicide Price Index Ratio	-1.270
	(4.016)
Nitrogen Price Index Ratio	-0.134
	(0.748)
Energy Price Index Ratio	0.181
	(0.463)
Time trend	0.023
	(0.015)
Cantonal dummies ^b	Yes
N	575
Pseudo R ²	0.21

Notes: * p<.1, ** p<.05, *** p<.01

^a Wheat price variable was centered as we also consider its squared value.

^b Cantonal results can be found in Online Appendix B.

Estimation results from the farming system choice were used to compute the inverse Mills ratio controlling for the potential selection bias in the input use demand equations. Results for the high- and low-input input demand equations are gathered in Table 3 and 4 respectively. The presence of selection bias seems to be confirmed for herbicide demand at least. The negative selection bias associated to low-input herbicide demand means that low-input farmers' unobserved characteristics tend to decrease their herbicide uses. On the other hand, the positive selection bias associated to conventional herbicide demand means that conventional farmers' unobserved characteristics tend to increase their herbicide uses.

Among observed characteristics, few seems to affect variable inputs demand. Globally, variable inputs demand in conventional production systems decreases by farm size. Yet, nitrogen fertilization demand increases with the share of winter wheat. This might indicate that winter wheat is more intensive in nitrogen fertilization than other crops. Otherwise, we find that conventional herbicide demand responds negatively to rainfall and positively to altitude. In low-input production system, we show that herbicide demand responds positively to being in a mountainous region. Indeed, mechanical weed control is easier to implement in plains than in sloped areas. At the same time, when controlling for the fact to belong to a

mountainous region, altitude negatively affects the herbicide demand for low-input farmers. This might indicate a lower level of weed competition when altitude is higher.

Table 3: Estimated inputs demand for conventional production system

	Nitrogen		Herbicide		Fungicide
Farm size	-0.531 *		-0.030 ***		0.006
	(0.305)		(0.012)		(0.009)
Share of winter wheat surface	117.499 ***		-1.725		0.729
	(43.195)		(1.279)		(1.079)
Mountain	22.604		0.032		0.068
	(14.704)		(0.409)		(0.334)
Altitude	-0.057		0.004 **		0.003
	(0.098)		(0.002)		(0.002)
Temperatures	12.951		-0.192		0.359
	(11.031)		(0.302)		(0.276)
Log(Rainfall)	-39.197		-1.210 ***		-0.734
	(26.979)		(0.459)		(0.689)
Herbicide Price Index Ratio	1854.597 **		-2.152		41.122 *
	(895.753)		(23.197)		(23.636)
Fungicide Price Index Ratio	-1723.428 **		0.685		-38.858 *
	(823.616)		(21.090)		(21.572)
Nitrogen Price Index Ratio	-316.471 **		0.978		-7.255 *
	(152.786)		(4.218)		(4.182)
Energy Price Index Ratio	160.289 **		-0.181		4.427 **
	(77.373)		(2.038)		(2.088)
Selection bias	-3.155		1.383 **		0.494
	(14.349)		(0.590)		(0.384)
Time trend	2.747		0.038		-0.090
	(3.254)		(0.076)		(0.078)
Intercept	-5196.968		-64.099		183.808
	(6432.161)		(148.922)		(152.696)
Cantonal dummies ^b	Yes		Yes		Yes

N	194	194	194
Adjusted R ²	0.16	0.17	0.05
AIC	2066.68	603.69	638.20
BIC	2138.57	675.58	710.09

Notes: * p<.1, ** p<.05, *** p<.01

^b Cantonal results can be found in Online Appendix B.

Standard errors are obtained using 100 bootstrap replications.

Table 4: Estimated inputs demand for low-input production system

	Nitrogen	Herbicide
Farm size	-0.054 (0.252)	0.010 (0.008)
Share of winter wheat surface	-36.522 (32.856)	0.650 (0.760)
Mountain	3.071 (7.873)	1.046 *** (0.310)
Altitude	0.024 (0.044)	-0.003 * (0.002)
Temperatures	-4.563 (4.846)	0.040 (0.223)
Log(Rainfall)	2.349 (17.407)	0.647 (0.900)
Herbicide Price Index Ratio	-156.667 (544.381)	-3.912 (28.167)
Fungicide Price Index Ratio	142.496 (502.278)	4.762 (26.293)
Nitrogen Price Index Ratio	22.059 (93.455)	-0.410 (4.633)
Energy Price Index Ratio	-15.250 (46.121)	0.649 (2.576)
Selection bias	12.889 (13.050)	-1.129 *** (0.430)

Time trend	2.653 (1.996)	-0.180 ** (0.092)
Intercept	-5157.399 (3953.248)	357.746 ** (180.992)
Cantonal dummies ^b	Yes	Yes
N	381	381
Adjusted R ²	0.14	0.23
AIC	3995.22	1527.94
BIC	4089.85	1622.56

Notes: * p<.1, ** p<.05, *** p<.01

^b Cantonal results can be found in Online Appendix B.

Standard errors are obtained using 100 bootstrap replications.

We can see significant differences between input demand price elasticities across production systems. First, in low-input production system, variable inputs demand is not significantly affected by price variables. The only exception is for nitrogen demand which increases when the herbicide price index ratio increase. Pesticides in low-input production system are one element among other and should only be used when there is no other option left (Lucas 2007). Given that, and assuming that herbicides are used parsimiously as they should in complement of mechanical pest control, the limited response to price variation is not surprising. To understand the impact of the herbicide price index ratio on the low-input nitrogen demand, we can mobilize the theory of opportunity costs. As aforementioned, the economic principle of low-input farming systems relies on cost reduction in a context of relative low crop prices. An increase in the herbicide price index results in a lower profitability of low-input production system and increases the opportunity cost of yield loss. A strategy could thus be to increase the level of fertilizers to try and increase the yield to avoid a profitability drop.

In conventional production system, we show a greater responsiveness of inputs demand to price variations. Both nitrogen fertilizers and fungicide demand are negatively impacted by an increase in fertilizer or fungicide price index ratios. On the other hand, they are positively impacted by an increase in herbicide or energy price index ratios. From an agronomic viewpoint, conventional production system was designed to achieve high target yield levels with high levels of fertilization and crop protection. If nitrogen fertilizers tend to trigger weed competition, they also tend to increase wheat susceptibility to diseases (Boquet & Johnson 1987; Henson & Jordan 1982; Howard et al. 1994; Lintell-Smith et al. 1992). An increase in the fertilizer price index might encourage farmers to be more parsimonious in their use, without impacting too much their yield level. As for the negative impact of the increase of fertilization price index ratio on the conventional fungicide demand, it can be fostered by agronomic and economic factors. First, by reducing their fertilization levels, conventional farmers might also reduce wheat susceptibility to disease (Howard et al. 1994; Lintell-Smith

et al. 1992). Hence a lower need for fungicides and a decrease in fungicide demand. Second, even if the yield reduction is limited, the decrease in revenue associated with a reduction in nitrogen fertilization might encourage the farmer to reduce his costs by reducing fungicide applications. The same reasoning can be applied when considering an increase in the fungicide price index.

On the other hand, despite triggering weed competition, an increase in the fertilizer price index does not negatively affect the herbicide demand. Statistics from Table 1, in particular the similar levels of herbicide use and mechanical pest control across production systems, might indicate that even conventional farmers make a parsimonious use of herbicides and use mechanical weed control as a substitute. Hence the relative inelasticity of the herbicide demand, even for conventional farmers. Such herbicide inelasticity also permits to understand why fungicide and nitrogen demands are positively affected by an increase in herbicide price index ratio. Indeed, such increase induces a higher opportunity cost of yield loss. As a response, and because of the inelasticity of herbicide demand, farmers may increase their fertilization level, as well as their fungicide uses, to try to increase their yield and absorb this herbicide price increase. The rationale behind the negative impact of a rise in the energy price index is analogous.

4.2. High and low-input production system specific production functions

Before estimating the production functions specific to each type of production system, we need to determine for each farming system the set of purely productive, interactive, and purely damage abating inputs. The agronomic principles of high- and low-input farming systems being different, we allow for these sets of inputs to differ across types of production practices. Herbicides, fungicides and mechanical pest control are considered as purely damage abating inputs. Thus, we need to determine among fertilizers and work and machinery which are productive inputs, if they belong to the set of purely productive inputs or if they need to be considered as interactive inputs. Based on Saha et al. (1997) separability tests, we consider (i) work and machinery as a purely productive input for both conventional and low-input functions (ii) fertilizers as a purely productive - respectively interactive - input for conventional function - respectively low-input function.¹² Then, based on Zhengfei et al. (2006), we perform asymmetry tests to see whether or not it is relevant to consider that inputs have an asymmetric role on the crop production or if their role is symmetric (i.e., we just need the productive part with all inputs as covariates). For both low-input and conventional farmers, results from the asymmetry tests confirm the asymmetric role of inputs.¹³

¹² Separability tests were also performed considering a quadratic and translog functional form for the production function. Results are robust across all specifications for the conventional production function. For the low-input function, result is robust when considering the quadratic specification while the translog specification concludes that there is no interactive input. Accordingly, a robustness check for low-input production function can be found in Online Appendix C with fertilizer considered as a purely productive input.

¹³ As for separability tests, we also performed the asymmetry tests considering a quadratic and translog functional forms. Results are robust when considering the translog specification. As for the quadratic specification, asymmetry test results do not permit to conclude as both hypotheses are rejected. Accordingly, we consider a symmetric specification for both functions as a robustness check in Online Appendix C.

Table 5 gathers the results from the conventional and low-input asymmetric production functions. First, for both conventional and low-input farmer, we notice that the coefficient associated to the corrected inverse Mills ratio is not statistically significant. It might indicate that selection bias only affects farmer yield through its impact on herbicide demand functions.¹⁴ Control function coefficients for input endogeneity are only significant in the low-input production function. As for inputs themselves, their effect on the conventional and low-input production functions seems to differ. While productive inputs have no significant impact on conventional yields, work and machinery is found to increase low-input yields. Nitrogen fertilizers are impacting low-input yields only through their interactive role in the damage abating part. Herbicide damage abating role is found to be significant in both conventional and low-input production functions.

Observed characteristics such as farm size and the share of winter wheat surface are not significantly affecting conventional nor low-input yields. However, being in a mountainous region has a positive impact on low-input yields. This might indicate that low-input production system is more profitable when cropping conditions are more difficult as in mountainous region. Table 5 also shows that conventional yields are sensitive to rainfall while low-input yields are rather sensitive to temperatures. This result can be interpreted considering the results on the probability to adopt the low-input production system. Rainfall decreases the probability to adopt low-input practices. Then we might argue that, in the perspective of high yield losses due to excessive rainfall, farmers would rather use fungicides, which mean being classified as a “conventional” farmer, to limit their losses.

Table 5: The estimated coefficients from the conventional and low-input production functions

	Conventional	Low-input
Farm size	-0.001 (0.002)	-0.000 (0.001)
Share of winter wheat surface	0.314 (0.220)	-0.163 (0.137)
Mountain	0.061 (0.070)	0.158 *** (0.053)
Altitude	-0.001 (0.001)	-0.000 (0.000)
Temperatures	-0.027 (0.106)	-0.123 *** (0.033)
Log(Rainfall)	-0.389 *** (0.127)	-0.033 (0.110)

¹⁴ Accordingly, we present the estimates from the high- and low-input production functions without inverse Mills ratio as robustness check in Online Appendix C.

Work and Machinery	-0.020 (0.120)	0.099 (0.049)	**
Nitrogen	-0.123 (0.101)	-0.124 (0.129)	
Nitrogen CF ^a	0.001 (0.001)	0.013 (0.003)	***
Herbicide CF ^a	0.006 (0.062)	0.147 (0.034)	***
Fungicide CF ^a	0.035 (0.070)		
Selection Bias	0.023 (0.463)	0.061 (0.090)	
Time trend	0.006 (0.009)	0.010 (0.008)	
Intercept (Productive)	-3.271 (16.500)	-6.327 (23.558)	
Mechanical Pest Control	-0.000 (0.000)	0.000 (0.000)	
Herbicides	0.052 * (0.031)	0.025 ** (0.012)	**
Fungicides	-0.089 * (0.056)		*
Nitrogen		0.002 * (0.001)	*
Intercept (Damage Abating)	0.097 (1.229)	2.545 * (2.214)	*
Cantonal dummies ^b	Yes	Yes	
N	194	381	
Adjusted R ²	0.07	0.18	
AIC	-71.78	-321.36	
BIC	19.72	-207.02	

Notes: * p<.1, ** p<.05, *** p<.01

^a CF = Control Function

^b Cantonal results can be found in Online Appendix B.

In here, we consider 250 bootstrap replications to ensure that our bootstrapped standard errors are obtained at least on 100 converging replications.

In Table 6, we compare the average marginal effect of inputs on the yields from three different specifications.¹⁵ Model (1) corresponds to the main specification of this article, i.e. the endogenous regime switching model with both selection bias and input endogeneity. Model (3) shows the results from a joint production function with no distinction according to the production system considered. Finally, model (2) is an in-between as we consider separate production functions for conventional and low-input farmers with no selection bias nor input endogeneity.

Table 6: Mean marginal effect of inputs on yields

Mean marginal effect on yields	Model (1)		Model (2)		Model (3)
	<i>Conventional</i>	<i>Low-input</i>	<i>Conventional</i>	<i>Low-input</i>	<i>All</i>
Work & machinery	-1.32	5.71**	-0.02	4.05	4.99**
Fertilizers	-7.93	-7.85	-0.28	-0.99	1.65
Mechanical pest control	-0.003	-0.009	-0.003	-0.008	-0.005**
Herbicide	0.58*	-8.32**	0.45	0.72	0.11
Fungicide	-0.99*		0.95		3.31****

Notes: * p<.1, ** p<.05, **** p<.01

Given the non-linear functional form of our production function, we cannot compute marginal effect of inputs on yields. We need to consider mean marginal effect, *i.e.* we consider the effect on yields when increasing the quantity of a particular input when other variables equal the sample average. As such, coefficients' direct interpretation is difficult as they heavily depend on other variables values.

First, we notice that contrary to model (1) and (3), there is no significant coefficients associated to input use in model (2). Considering separate conventional and low-input production function is not enough: selection bias and input endogeneity should be accounted for. While the comparison with the separate functions with no selection bias nor input endogeneity suffers from the lack of significant coefficients, the joint production function comparison is insightful. Model (3) shows a positive effect of additional work and machinery on yields. Yet, model (1) shows that this positive effect of work and machinery only affects the low-input production function. In the conventional case, we do not find a significant effect of work and machinery on yields. The positive mean marginal effect of fungicide on yield from model (3) becomes negative for conventional producers when considering model (1). Model (1) and model (3) also gives different results in terms of significance. Unlike separate functions, the joint production function allows to show a significant mean marginal effect of mechanical pest control on yields. On the other hand, model (1) shows a significant (and

¹⁵ The mean marginal effects are not directly interpreted. We are rather interested in comparing the effect of different production function specifications on the sign and significance of these parameters.

opposite) mean marginal effect of herbicides on conventional and low-input yields. In model (3), herbicide mean marginal effect is not statistically significant.

Overall, our results advocate for considering both selection bias and input endogeneity when estimating production function when farmers are using different production systems. One should not empirically assess the effects of the adoption of the low-input practices on input uses and yields without considering selection and input endogeneity issues. This is in line with previous findings from the literature, e.g., Pietola and Lansink (2001) who advocate for an adverse selection issue for agri-environmental programs as adopters have lower yields at baseline. In particular, our results show that, in the Swiss case, the low-input production system is adopted by younger and more educated farmers with smaller farm and more diversified source of revenue, as previously highlighted by Finger and El Benni (2013). Hence, if the Swiss extenso program seems to be successful as it is well-diffused among farmers, our findings show its impact on pesticide use is limited as it was adopted with farmers with already lower input use levels. Plus, pesticide savings mainly concern fungicide uses but are very limited when considering herbicide uses. Yet, herbicides also have a negative impact on the environment. A cost-benefit analysis of the existing Extenso program should be considered. Whereas the question on an herbicide-free Extenso program has been raised (Böcker et al. 2019; Böcker & Finger 2018), the question on how to encourage the reluctant conventional farmers to adopt the low-input production system seems to remain. In particular, from our descriptive statistics we find that low-input farmers benefit from similar, if not superior, economic returns. Hence the need for a more thorough investigation into the factors that explain such a lock-in could help to design policy instruments that would specifically target the "laggards".

5 Conclusion

This paper investigates the production function of low-input production systems compared to conventional ones. We consider observational data from Swiss wheat producers. To investigate and account for the potential selection bias in production system choice, we consider an endogenous regime switching model combined with control functions to account for input endogeneity. We find selection bias for both the conventional and low-input herbicide demand, meaning that unobservables that are affecting the choice of production practices are also affecting the level of herbicide demand for farmers. At the same time, we find endogeneity in farmers input choices, meaning that unobservables affecting inputs demand are also impacting the observed yields. Finally, we find that both biases are interlinked, and highlight the need to account for both selection bias and endogeneity.

Our article also highlights a few differences across the conventional and low-input wheat production systems when accounting for their differences in estimation. First, input demands of low-input farmers seem to be rather inelastic to relative price of inputs. On the other hand, input demands of conventional farmers, particularly nitrogen and fungicide demand, vary in function of the relative price of inputs. Second, production functions also display significant differences across conventional and low-input production systems. First, the role of inputs –

e.g., productive, damage abating or interactive – in the production function varies across production systems. In the low-input production system, nitrogen fertilizers and herbicides have a significant interactive effect on pest control. By triggering weed competition, nitrogen fertilizers affect the productivity of herbicides. Whereas in conventional system, this interactive effect does not appear as statistically significant. As for the effect of inputs and other factors on yields, our approach permits to highlight differences across production systems. For instance, conventional yields are significantly impacted by rainfall while low-input yields rather seem to respond to temperature variations. The highlighted differences in the high- and low-input production functions are robust across the different specifications we tested in Online Appendix C.

Such differences in the farmer's inputs demand and production function are worth accounting for when designing pesticide public policies. For instance, pesticide taxation policies, especially if targeting herbicide uses, might have a more harmful effect for low-input farmers than conventional ones. Inputs demand of low-input farmers being inelastic to input prices, a tax would result in an increase in their production cost. On the other hand, conventional farmers can adjust their input demand to input price variations to limit the impact of such taxation policy on their profitability. If not differentiated across production system, a pesticide taxation policy could reduce the low-input production system profitability and potentially encourage the adoption of conventional production system. More globally, because of the differentiated role they play on low-input and conventional yields, we need to assess separately the impact of any pesticide policy impacting the use of variable inputs.

Future research could expand our modelling framework in two main directions. First, future research may account for the panel nature of datasets with farm-level observations. Our modelling framework mostly ignores the panel dimension of our dataset. We try to account for the panel dynamics in our models by including a time trend while the canton dummies try to account for "individual" heterogeneity.¹⁶ Except for the low-input herbicide demand, it seems that there is no time trend in low-input adoption, input demand or observed yield. Yet, our assumption on the functional form of the error terms fully ignores the panel dimension of our dataset. We assume that the choice of cropping practice is independent across farmers but also across time. Despite the flexibility of the Swiss Extenso program, it remains highly unlikely that the farmer choice to adopt low-input practices is independent across time.¹⁷ Similarly, we do not directly account for the panel dimension of our dataset in the error terms of the input demand functions or in the error terms of the production functions. An extension of the Carlson generalized two-step Heckman estimator (2022) to our endogenous regime switching model would allow for heteroskedastic error terms. Such extension would allow for autoregressive error terms to investigate the time-interdependence of the low-input adoption decision as well as farmer's input demands and yields.

¹⁶ We choose a time trend approach over year fixed-effects as the introduction of year fixed-effects captures price and weather variations simultaneously. Yet, we need prices as instrumental variables to build our control functions to account for input endogeneity.

¹⁷ Indeed, entering the Extenso program is not binding for the farmer. At any time between or even during cropping season, he could decide to quit the program so he could use fungicides and insecticides. Switching back to conventional production system does not prevent him to benefit from the program in the future.

Second, future research shall consider entire crop rotations, not single crops. We here consider low-input practices rather than low-input farming systems because our data is limited to winter wheat. Only investigating winter wheat means that we neglect the affects and adaptations introduced using different crop rotation, which is especially important for low-input farming systems. Considering a multicrop approach would allow to (i) integrate the crop rotation effects in our model while (ii) investigating the extensive margin impact of public policies implementing taxes or subsidies on pesticides. Indeed, such policies might impact the intensive margin through the choice of production practices and input uses but might also conduct the farmer to change the crops he is cultivating as well as the share attributed to each culture (Möhring, Dalhaus, et al. 2020).

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Data Availability

The data supporting this study's findings are provided by Agroscope—the Swiss Federal center of excellence for agricultural research. The farm-level data is confidential and thus cannot be made publicly available. Stata code for the analysis performed in the manuscript is available in online supplementary material.

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