



**AgEcon** SEARCH  
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

# Fungicide use under risk in Swiss wheat production

Nikolaus Gotsch<sup>a,\*</sup>, Uri Regev<sup>b</sup>

<sup>a</sup> *Swiss Federal Institute of Technology (ETH), Institute of Agricultural Economics, ETH Zentrum, CH-8092 Zurich, Switzerland*

<sup>b</sup> *Ben-Gurion University of the Negev, The Monaster Center for Economic Research, Beer-Sheva 84105, Israel*

Accepted 11 December 1995

---

## Abstract

The short-run effects of fungicide application on economic risk and the effects of risk on fungicide use in Swiss wheat production are empirically explored. A quadratic production function model is developed. With the help of the moment-based approach, marginal contributions of fungicides (representing controlled inputs) and of rain (representing uncontrolled inputs) to the variances of yield and revenue are analyzed.

It is not possible to show risk-reducing effects of fungicides on yield or revenue. At low rain quantities during the vegetation period fungicides have a statistically significant risk-increasing effect on revenue. Increasing risk leads Swiss wheat growers to use more fungicide. This increase is statistically significant at higher levels of revenue. For example, when risk is doubled fungicide inputs are raised by 44% at the highest revenue quartile.

---

## 1. Introduction

Pest damages are influenced by many factors that cannot be foreseen or controlled by the farmers so that yield and farm income are subject to many forms of uncertainty. Farmers often expect chemical pesticides to be risk-reducing since they quickly reduce pests and diseases and thus pesticides are even used as a 'form of insurance' (Mumford and Norton, 1987). Therefore, higher risk will lead to higher pesticide use (Feder, 1979; Pingali and Carlson, 1985). Regev (1994) has theoretically demonstrated that production uncertainty can cause both an increase or a decrease in the pesticide application rate depending on the type of uncertainty involved. Many empirical works support ambiguous results regarding the relation of risk and pesticide use

(Greene et al., 1985; Moffitt, 1986; Horowitz and Lichtenberg, 1994). A survey of the literature on risk in pest control decision making is given by Pannell (1991).

The first part of this article tests empirically if fungicide application in Swiss wheat production increases or reduces risk. The second part explores how risk attitudes of the farmers affect the response of fungicide use to changes in environmental factors (in particular, rain). The third part of this article analyses the effects of increasing risk on the fungicide application rate.

## 2. Modeling risk

### 2.1. Risk in conventional production function analysis

Conventional production function analyses impose strong restrictions on the probability distribu-

---

\* Corresponding author at: Institute of Agricultural Policy and Market Research, Justus-Liebig-University Giessen, Senckenbergstrasse 3, D-35390 Giessen, Germany.

tion of the output and imply biases on risk effects of the inputs. For example, using the familiar Cobb–Douglas production function one incorrectly imposes risk-increasing effects of all inputs, and as a result, the optimal level of inputs (and output) must increase (Just and Pope, 1978). Consequently, incorrect conclusions are drawn in evaluating policies, i.e. a pesticide control which may imply increased risk, but actually the utility loss of a risk averse farmer will be greater than the one incorrectly estimated.

Just and Pope (1978) suggest the following alternative formulations to overcome this problem:

$$Q = f(X) + h(X) \cdot \epsilon, E(\epsilon) = 0, V(\epsilon) = \sigma$$

or

$$Q = f(X)h(X \cdot \epsilon)$$

where  $Q$  is output,  $X$  is a vector of inputs and  $\epsilon$  is a random error variable.

Antle (1983) shows that the restrictions imposed by conventional Cobb–Douglas production function are such that the  $i$ th moment elasticity with respect to any input is proportional to the first moment elasticity. That is

$$\eta_{ik} = \frac{\partial \mu_i}{\partial x_k} \frac{x_k}{\mu_i} = i\eta_{ik}$$

where  $\mu_1 = E(Q)$ , and  $\mu_i$  is the  $i$ th moment about the mean. The other commonly used function  $Q = f(X) + u$ , for any  $f$  which is linear in the parameters (such as polynomial function of any degree), the restriction is  $\eta_i = 0$  for  $i \geq 2$ . Antle (1983) further shows that though the variance of Just and Pope (1978) is free of restrictions, higher moments are not, since in their model  $\eta_{ik} = i\eta_{2k}/2$  for  $i \geq 3$ .

## 2.2. The moment-based approach

The moment-based approach (Antle, 1983) is used for our econometric model in order to estimate the effects of risk on the choice of pest management strategy (the quantity of pesticide input), as well as to try to answer empirically whether or not chemical pesticides are found to be risk-reducing in our sample.

The moment-based model is summarized as follows.

Let  $Q_j$  be the output of the  $i$ th firm,  $x_j = (x_{j1}, \dots, x_{jk})$  be the input vector, and  $u_j$  be a random error with zero mean. The production function of the  $i$ th firm is

$$Q_j = x_j\gamma_1 + u_j, \mu_{1j} = E(Q_j) = x_j\gamma_1, j = 1, \dots, N \quad (1)$$

Define  $\mu_{ij} = E(u_j^i)$  for  $i \geq 2$ , as the  $i$ th moment of  $Q_j$  about its mean  $\mu_{1j}$ , i.e.  $\mu_{ij} = E[Q_j - E(Q_j)]^i$ . The main element of the approach is the assumption that higher moments of the distribution also depend on the input vector:

$$u_j^i = x_j\gamma_i + v_{ij}, E(v_{ij}) = 0, E(u_j^i) = \mu_{ij} = x_j\gamma_i, \quad i \geq 2 \quad (2)$$

The model implies a different parameter vector  $\gamma_i$  for each moment function and does not impose the above mentioned restrictions on the distribution function. Given the usual assumptions on the errors of the regression, except homoscedasticity, the least square estimator of Eq. (1),  $\hat{\gamma}_1$ , is a consistent estimator of  $\gamma_1$  and the residuals of this regression are

$$\hat{u}_j = u_j + x_j(\gamma_1 - \hat{\gamma}_1) \quad (3)$$

$\text{plim} \hat{u}_j^i = u_j^i$  for all  $i$ , and  $\text{plim} \hat{\gamma}_i = \gamma_i, i \geq 2$ .

Furthermore

$$E(u_j^2) = \mu_j^2, E(v_{ij}^2) = \mu_{2i,j} - \mu_{ij}^2 \quad (4)$$

Then one can obtain consistent estimates of  $\mu_{ij}$  (denoted  $\hat{\mu}_{ij}$ ) by using least square regressions for Eq. (1) and Eq. (2). As shown by Eq. (4), the error terms  $u_j$  and  $v_{ij}$  are heteroscedastic and their variances are functions of the inputs; thus, GLS regressions of Eq. (1) and Eq. (2) with weights given by  $(\hat{\mu}_{2j})^{-0.5}$  and  $(\hat{\mu}_{4j} - \hat{\mu}_{2j}^2)^{-0.5}$  respectively, are feasible and consistent.

## 2.3. The empirical model

We have adopted a quadratic model with an additive error term, which allows sufficient flexibility of the results and avoids the restrictions for the stochastic errors. Based on the available data, wheat output is regressed on the quadratic form of the

following variables: APPL, NITRO, CCC, RAIN, and dummy variables for the year effect (notation is:

and definitions appear in Table 1). Thus, the model is:

$$\begin{aligned} \beta \cdot x_j + u_j = \sum \beta_i \cdot x_{ij} + u_j = & \beta_1 + \beta_2 \cdot \text{APPL}_j + \beta_3 \cdot \text{NITRO}_j \\ \text{YIELD}_j = & + \beta_4 \cdot \text{CCC}_j + \beta_5 \cdot \text{RAIN}_j + \beta_6 \cdot \text{AA}_j + \beta_7 \cdot \text{NN}_j + \beta_8 \cdot \text{CC}_j + \beta_9 \cdot \text{RR}_j \\ & + \beta_{10} \cdot \text{AN}_j + \beta_{11} \cdot \text{AC}_j + \beta_{12} \cdot \text{NC}_j + \beta_{13} \cdot \text{AR}_j + \beta_{14} \cdot \text{NR}_j + \beta_{15} \cdot \text{CR}_j \\ & + \beta_{16} \cdot \text{Y84}_j + \beta_{17} \cdot \text{Y85}_j + \beta_{18} \cdot \text{Y86}_j + \beta_{19} \cdot \text{Y88}_j + \beta_{20} \cdot \text{Y91}_j + U_j \end{aligned} \quad (5)$$

where  $x_{ij}$  ( $i = 1, \dots, 20$ ;  $j = 1, \dots, 908$ ) are the explanatory variables as given by the right-hand side of the equation, and  $\beta_i$  are unknown parameters. The input variables can be divided into two categories: controlled inputs (APPL, NITRO, CCC) and uncontrolled or environmental inputs (RAIN, and Y84, ..., Y91). The year dummy variables are shifters of the constant term, so that each of their coefficients indicates by how much the yield for the specific year differs from that of 1987 (arbitrarily selected and its constant term is  $\beta_1$ ).

The empirical model is based on 908 observations, obtained as follows. Wheat production data of 561 fields from the EPIPPE (a supervised disease and pest warning system for winter wheat) for the years 1984–1988 was obtained from the Swiss Federal Station of Agronomy Zurich Reckenholz. The participating farmers collect their own field data.

These are entered into a computer program, which produces recommendations for treatments for each individual field. In addition, 347 observations sampled from the 1991 production year were collected by the authors with the help of a written on-farm survey. Pluviometric data from electronic data bases of the Swiss Meteorological Institute in Zurich were assigned to each field. A more detailed description of the data used is provided by Gotsch et al. (1993).

The interpretation of the individual parameters of the quadratic model is in general not important, since the crucial interest here is in estimation of the marginal productivity of the inputs. This is the partial derivative of the yield with respect to a specific input and is given by a linear combination of the parameter vector. For example, the marginal productivity of APPL (MPA) is given by:

$$\begin{aligned} \text{MPA} = \partial \text{YIELD} / \partial \text{APPL} = & \beta_2 + 2\beta_6 \cdot \text{APPL} + \beta_{10} \cdot \text{NITRO} + \beta_{11} \cdot \text{CCC} \\ & + \beta_{12} \cdot \text{RAIN} \end{aligned} \quad (6)$$

From Eq. (6) it can be seen that the value and standard error of any marginal productivity depend on the values of the four inputs, and can be calculated. The first column of Table 2 shows the marginal productivity of fungicide applications and their standard error at various levels of rain, all other inputs held constant at sample average. Being a linear combination of the betas, statistical tests and significance levels of the marginal productivity are obtainable and presented in the Section 3 for sample average values of the inputs (nitrogen and tiller shortener).

The unobserved errors  $U_j$  are assumed to be

normally distributed with zero mean. Unlike the conventional regression model, it is assumed here that the variance of  $U_j$  depends also on the inputs. It is further assumed that this dependence takes the same functional form as the production function. Thus, the estimated errors of the production function are squared and regressed on the above inputs in the same form as the original regression.

The estimated values of this regression are the estimated variances of the yield in the  $j$ th observation, denoted  $\hat{\mu}_{2j}$ . The marginal contribution (partial derivatives) of the various inputs in this second regression are obtained in a similar way to those in

Table 1  
Notation and definitions of variables

| Notation | Definition   |
|----------|--|
| APPL     | Number of fungicide applications                                 |
| NITRO    | Total quantity of mineral nitrogen (kg N ha <sup>-1</sup> )      |
| CCC      | Number of tiller shortener applications                          |
| RAIN     | Quantity of rain between 1 March and 2 weeks before harvest (mm) |
| AA       | APPL × APPL  |
| NN       | NITRO × NITRO  |
| CC       | CCC × CCC  |
| RR       | RAIN × RAIN  |
| AN       | APPL × NITRO   |
| AC       | APPL × CCC   |
| NC       | NITRO × CCC  |
| AR       | APPL × RAIN  |
| NR       | NITRO × RAIN   |
| CR       | CCC × RAIN   |
| Y84–Y91  | Dummy variables for the years                                    |
| YIELD    | Wheat grain yield (dt ha <sup>-1</sup> )                         |

the first regression, but they are interpreted here as marginal contribution of the inputs to the variance of the yield, that is their risk-increasing or decreasing effect (if the sign is positive or negative). All other conventional statistical assumptions on the errors are kept, i.e.  $(u_j) = 0$  and  $(u_j u_1) = 0$  for  $j \neq 1$ .

The basic assumption of the moment-based approach is that higher moments of the distribution depend on the input vector. This implies that the error terms of the model are heteroscedastic. This means that the ordinary least squares method, though yielding consistent estimates, is not efficient, and the generalized least squares approach yields efficient estimates. This estimation procedure amounts to weighing the observations in the model estimating the first moment by  $\hat{\mu}_{2j}$  and the second moment by  $w_j = \hat{\mu}_{4j} - \hat{\mu}_{2j}^2$ , respectively (the estimated variance of the error terms), as given above. The variable  $\hat{\mu}_{4j}$  is obtained by regressing  $\hat{U}_j^4$  on the input vector. However, in practice, both  $\hat{\mu}_{2j}$  and  $w_j$  can involve some negative values, which contradict the notion of variance. In our empirical results,  $\hat{\mu}_{2j}$  was positive everywhere and only relatively few negative values of  $w_j$  (less than 10%) were estimated, and these observations were omitted from the analysis. A pilot study that did not use the GLS has shown only slight changes in the results.

Another type of analysis possible from this model

is comparative static estimation of the effects of change in environmental inputs on the controlled inputs, and the impact of risk attitudes of the growers on this reaction. In a deterministic context, the three controlled inputs (fungicide, nitrogen and tiller shortener) give three optimum conditions equating marginal productivities to the respective input prices. Taking derivatives of these conditions with respect to rain (or any other non-controlled or environmental input in the model) gives three equations, which can be written in a matrix notation:

$$\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} dx_1/dx_4 \\ dx_2/dx_4 \\ dx_3/dx_4 \end{bmatrix} = \begin{bmatrix} -f_{14} \\ -f_{24} \\ -f_{34} \end{bmatrix} \quad (7)$$

where the subscripts 1, ..., 4 denote the four variables fungicide, nitrogen tiller shortener and rain respectively, and  $f_{ij}$  is the cross partial derivative of the yield with respect to the  $i$ th and  $j$ th inputs. The solution of these equations gives the required comparative static results in a deterministic model. The results are presented in percentage changes, using  $(dx_i/x_i)/(dx_4/x_4)$ .

When farmers are risk averse, the first order conditions include 'risk premium' so that  $mp_i - k \cdot mv_i - w_i = 0$ , where  $mv_i$  is the change in output variance resulting from a small change in input  $i$ ,  $w_i$  is the normalized price of input  $i$  (normalized by output price) and  $k$  is a risk premium parameter which is Pratt's absolute risk aversion coefficient divided by 2 (see Antle, 1987). Accordingly, for a risk averse farmer with a risk aversion parameter  $k$ , the effect of an environmental factor on his behavior  $(dx_i/dx_4)$  will now be given by the solution of the following set of equations:

$$\left( \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} - k \cdot \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix} \right) \begin{bmatrix} dx_1/dx_4 \\ dx_2/dx_4 \\ dx_3/dx_4 \end{bmatrix} = \begin{bmatrix} -f_{14} \\ -f_{24} \\ -f_{34} \end{bmatrix} \quad (8)$$

where  $g_{ij}$  are the cross partial derivatives of the variance with respect to the  $i$ th and  $j$ th inputs. Thus, for a given value of the risk aversion parameter  $k$ , the solution of the equation gives the reaction of the farmers to environmental or other non-controlled inputs. The results of this analysis are presented in the next section for a range of risk parameter values obtained from the risk literature.

### 3. Results

#### 3.1. Analysis of marginal productivities

Table 2 presents the estimated marginal productivity and the values of marginal productivity for fungicide applications for a range of rain quantities between 350 and 550 mm, all other variables at their sample average values. The value of marginal productivity is interpreted as the additional revenue obtained by applying an additional fungicide application. These values are significantly different from zero, and quite reliable with a 95% confidence interval. Values of marginal productivity and marginal productivities are very close to one another since average price for wheat is sFr. 1.04 kg<sup>-1</sup> and its standard error is 0.025.

In order to analyze the effect of environmental change on fungicide applications, the usual assumptions of maximizing behavior are required. That is, farmers are price takers and maximize profits in a competitive framework. However, it is important to notice that wheat quality (and price) is affected by grain humidity and shows changes over the sample years. The price decreases with grain humidity, approximately a 1% reduction for every percent increase in grain humidity. Since wheat price is affected by quality it is clear that in our optimization and comparative static analysis we have to use revenue

rather than yield. Thus the usual necessary condition for optimization holds with fixed prices. The effect of change in rain quantities on the optimal levels of fungicide use is analyzed by comparative static calculations (Eq. (7)). The results are presented in the last column of Table 2. The entries give the percentage change of fungicide application corresponding to a 1% change in rain quantity. The values are given for a range of rain quantities between 350 and 550 mm. The results show that optimal values for fungicide application decrease. These values decrease from -0.7 for rain = 350 mm to -1.2 for rain = 550 mm, so that a 10% increase in rain will reduce fungicide applications by 7–12%, depending on rain quantities.

#### 3.2. Effects of pesticide use on risk

In the context of the normal distribution assumed by the model, the variance could be used as an index of risk. Thus, adopting the definition of risk of Rothschild and Stiglitz (1970) as a mean preserving spread, higher variance implies higher risk if a given expected yield is maintained.

Table 3 presents the marginal contribution of fungicide application to the variance, which shows that fungicide application, which is expected to be risk-reducing and even used as a 'form of insurance' (Mumford and Norton, 1987), is found to be significantly positive, and thus risk-increasing for at least the lower and average rain levels.

The next question to be addressed was how farmer's risk attitudes affect his response to environmental changes. According to the discussion in Section 2.3, the Pratt absolute risk aversion parameter reflects the risk attitudes of decision makers. Estimates of this parameter in the literature are between 0.5 and 1.5 (Antle, 1987), and accordingly we esti-

Table 2  
Marginal productivity, value of marginal productivity, and elasticity of fungicide applications with respect to rain quantity at different levels of rain (standard errors in parentheses)

| Rain quantity (mm) | Marginal productivity (dt grain yield per application) | Value of marginal productivity (100 sFr. revenue per application) | Elasticity of fungicide with respect to rain |
|--------------------|--|---|--|
| 350                | 2.2411 (0.5812)  | 2.2470 (0.5951)   | -0.761                                       |
| 400                | 2.4073 (0.4832)  | 2.4418 (0.4936)   | -0.870                                       |
| 450                | 2.5735 (0.4274)  | 2.6366 (0.4351)   | -0.979                                       |
| 500                | 2.7397 (0.4307)  | 2.8314 (0.4373)   | -1.087                                       |
| 550                | 2.9059 (0.4919)  | 3.0262 (0.4995)   | -1.196                                       |

Table 3  
Marginal contribution of fungicide applications to revenue variances at different rain quantities (*t*-values in parentheses)

| Rain quantity (mm) | Marginal contribution of fungicide application to revenue variances ((100 sFr.) <sup>2</sup> per application) |
|--------------------|---|
| 350                | 15.298 (2.11)   |
| 400                | 12.749 (2.14)   |
| 450                | 10.200 (2.03)   |
| 500                | 7.650 (1.62)  |
| 550                | 5.101 (0.99)  |

mated the response of farmers to environmental changes for this range of values. From our data we could measure environmental effect by rain quantities. Results in Table 4 give the response of fungicide application to changes in rain quantities (in elasticity terms) for a range of rain quantities between 350 and 550 mm. It is interesting to see that for the range of risk attitudes assumed here ( $0.5 < k < 1.5$ ), elasticities are not sensitive to the risk aversion parameter. However, the elasticities decrease from approximately  $-1.0$  to  $-1.6$  when rain increases from 350 to 550 mm. This means that risk-averse farmers react to a marginal 1% increase in rain by reducing fungicide by approximately 1–1.6%. These results can be compared with those in the last column of Table 2 (reproduced here for convenience) where farmers are assumed to be risk neutral ( $k = 0$ ), or that there is no risk involved. This comparison shows that risk-averse farmers are more sensitive to changes in rain than risk-neutral farmers, and the elasticities are 30–40% higher (in absolute values). It is important to note that the reliability of these empirical findings is not ascertained, since the elasticity is not a linear combination of the parame-

Table 4  
Elasticities of fungicide application with respect to different rain quantities and different values of the risk aversion parameter *k*

| Rain (mm) | Risk aversion <i>k</i> |        |        |        |
|-----------|------------------------|--------|--------|--------|
|           | 0                      | 0.5    | 1.0    | 1.5    |
| 350       | -0.761                 | -1.020 | -1.008 | -1.003 |
| 400       | -0.870                 | -1.166 | -1.152 | -1.146 |
| 450       | -0.979                 | -1.312 | -1.296 | -1.290 |
| 500       | -1.087                 | -1.458 | -1.440 | -1.433 |
| 550       | -1.196                 | -1.604 | -1.584 | -1.576 |

ters. Nevertheless, this type of comparative static analysis could be methodologically meaningful and should be checked for other data and situations.

### 3.3. Effects of risk on optimal pesticide use

The effect of increasing risk on optimal behavior of farmers is discussed in the literature, and is pertinent to policy decision-making. It is addressed here since risk is estimated in the model by variance as a function of fungicide applications. In order to estimate the effect of increasing risk on input use, it was necessary to obtain the stratification of the variance for a fixed average revenue. This was done by dividing the sample into four quartiles of variance and four quartiles of revenue. The observations in each revenue quartile are divided into those belonging to the highest variance quartile (averaging 102.3) and those belonging to the lowest variance quartile (averaging 43.5). Thus the difference of input quantities in these two subsamples are related to the risk effect.

Table 5 presents results on the effect of increasing risk on optimal fungicide application. For revenue lower than average (revenue quartiles 1 and 2) increasing risk does not significantly increase fungicide application, but it never decreases it. The third line of the table gives the number of observations with low and high variance for each quartile. The fourth line gives its average. In the fifth line, differences in input values between high and low variance are calculated (standard errors given in parentheses). The effects of risk on optimal input use are calculated in elasticity terms, namely  $\frac{\Delta \text{input}}{\text{av. input}} / \frac{\Delta \text{variance}}{\text{av. variance}}$ , which is repeated for every revenue quartile (the appropriate averages appear in Table 6). These results show that fungicide reaction to increasing risk goes from 0.12 in the second quartile to 0.44 in the highest quartile. This means that for the highest range of revenues an increase of 1% in risk increases fungicide application by 0.44%. Examining the standard errors in the fifth line, we find that the increase in fungicide application due to increasing risk is quite reliable and significantly positive for the upper two quartiles of revenue. Thus, to achieve

Table 5  
Effects of increasing risk (variance of revenue) on optimal fungicide application

|   | Rev. quart. 1 |               | Rev. quart. 2 |               | Rev. quart. 3 |               | Rev. quart. 4 |               |
|---|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
|   | Var. quart. 1 | Var. quart. 4 | Var. quart. 1 | Var. quart. 4 | Var. quart. 1 | Var. quart. 4 | Var. quart. 1 | Var. quart. 4 |
| No. of observations   | 87            | 21            | 75            | 21            | 32            | 57            | 11            | 105           |
| Av. no. of fungicide applications   | 0.92          | 1.10          | 1.03          | 1.19          | 1.03          | 1.39          | 0.91          | 1.45          |
| $\Delta$ Av. no. of fungicide applications                                |               | 0.18 (0.20)   |               | 0.16 (0.18)   |               | 0.36 (0.16)   |               | 0.54 (0.22)   |
| Av. revenue variance ((100 sFr.) <sup>2</sup> ha <sup>-1</sup> )          | 42.8          | 102.8         | 43.7          | 99.6          | 44.8          | 100.4         | 44.4          | 103.8         |
| $\Delta$ Av. revenue variance ((100 sFr.) <sup>2</sup> ha <sup>-1</sup> ) |               | 60.0 (2.8)    |               | 55.9 (2.2)    |               | 55.6 (2.2)    |               | 59.4 (2.3)    |
| Elasticity of fungicide application with respect to variance of revenue   |               | 0.142         |               | 0.118         |               | 0.255         |               | 0.439         |

Rev. quart., revenue quartile; var. quart., variance quartile.  
Standard errors are given in parentheses.



Table 6  
Averages for revenue and fungicide applications, at the four revenue quartiles

| Revenue quartile | Revenue average<br>(100 sFr. ha <sup>-1</sup> ) | Fungicide application average<br>(no. of applications) |
|------------------|---|--|
| 1                | 49.4  | 0.96   |
| 2                | 59.9  | 1.01   |
| 3                | 67.8  | 1.22   |
| 4                | 77.6  | 1.42   |

higher revenue, farmers react to increasing risk by increasing fungicide applications and the higher the revenue the greater is this response.

#### 4. Conclusions

This paper focuses on the risk behavior of wheat growers. Our first observation was that yield variance and revenue variance were not found to differ much, which can be explained by the guaranteed price system.

Analyzing the risk effect on fungicide input demonstrated that fungicides are not risk-reducing. Furthermore, fungicides are found to be risk-increasing for low rain quantities. These findings should appease Swiss farmers, who fear that official policy recommendations promoting reduced fungicide application will increase their production risk.

An important finding is that increasing risk leads Swiss wheat growers to use more fungicides. That is, it was found that farmers with a given average revenue and high variance used more of that input than growers with the same average revenue but lower variance. This result is prominent for higher revenue ranges, where at the highest revenue quartile fungicide applications are raised by 44% when risk is doubled.

The econometric model did not allow an analysis of varying input timing. In particular, it did not discriminate between early and late fungicide applications or uncontrollable climatic events such as early or late rainfall during the vegetation period. The effects of these dynamic aspects on risk should be further explored and analyzed in a different framework.

#### Acknowledgements

The authors are indebted to Dr. Hans-Rudolf Forrer, Swiss Federal Station of Agronomy, Zurich Reckenholz, Switzerland, who enabled us to use the EPIPRED data and enhanced our knowledge of wheat agronomy and disease pathology.

We would like to thank those who provided addresses of Swiss farmers to make the production survey possible (Biofarm-Genossenschaft, BIO Gemüse, Swiss Federal Office of Statistics).

The authors also like to thank the Swiss Meteorological Institute, Zurich, for making available pluviometric and climatic data and to Dr. Mario Rohrer and Dr. Ludwig Braun, Department of Geography, ETH Zurich, who enabled us to efficiently transfer the data to PC. We are also grateful to the anonymous referee for his helpful comments.

This project was funded by ETH Zurich, Switzerland and supported by the Institute of Economics, Monaster Center, Ben-Gurion University, Beer-Sheva, Israel.

#### References

- Antle, J.M., 1983. Testing the stochastic structure of production: A flexible moment-based approach. *J. Bus. Econ. Stat.*, 1: 192–201.
- Antle, J.M., 1987. Econometric estimation of producers' risk attitudes. *Am. J. Agric. Econ.*, 69: 509–522.
- Feder, G., 1979. Pesticides, information and pest management under uncertainty. *Am. J. Agric. Econ.*, 61: 97–103.
- Gotsch, N., Regev, U. and Rieder, P., 1993. Economic evaluation of pest management decisions in Swiss wheat production. ETH, Zurich, Switzerland.
- Greene, C.R., Kramer, R.A., Norton, G.W., Rajotte, E.G. and McPherson, R.M., 1985. An economic analysis of soybean integrated pest management. *Am. J. Agric. Econ.*, 67: 567–572.
- Horowitz, J. and Lichtenberg, E., 1994. Risk-reducing and risk-increasing effects of pesticides. *J. Agric. Econ.*, 45: 82–89.
- Just, R.E. and Pope, R., 1978. Stochastic specification of production functions and economic implications. *J. Econometrics*, 7: 67–86.
- Moffitt, L.J., 1986. Risk-efficient threshold for pest control decisions. *J. Agric. Econ.*, 37: 69–75.
- Mumford, L. and Norton, G., 1987. Economic aspects of integrated pest management. In: V. Delucchi (Editor), *Integrated Pest Management-Quo Vadis? Parasitism*, Geneva, pp. 397–407.
- Pannell, D.J., 1991. Pests and pesticides, risk and risk aversion. *Agric. Econ.*, 5: 361–383.

Pingali, P.L., Carlson and G.A., 1985. Human capital, adjustments in subjective probabilities, and the demand for pest controls. *Am. J. Agric. Econ.*, 67: 853–861.

Regev, U., 1994. The effects of uncertainty on pesticide use and

the choice of pest management strategies. Monaster Economic Research Center, Ben-Gurion University, Beer-Sheva, Israel.

Rothschild, M. and Stiglitz, J.E., 1970. Increasing risk: I. A definition. *J. Econ. Theory*, 2: 225–243.

