EFFECTIVENESS OF ORGANIC CERTIFICATION: A STUDY ON AN ITALIAN ORGANIC CERTIFICATOR'S DATA

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134th EAAE Seminar

Labels on sustainability: an issue for consumers, producers, policy makers, and NGOs

Abstract

The aim of this paper is to implement risk-based models for the inspection procedures in the organic certification. Organic products have a specific regulation concerning labelling at the European level. The European organic logo assures that products are obtained respecting common standards set by organic regulation. The implementation of the certification is delegated to national and regional competent authorities, which then assign the inspection and certification procedures to accredited and approved control bodies. A risk-based approach, that could inform control bodies in planning inspections, can contribute to a more efficient and cost-effective certification system. Our analysis is based on a dataset obtained from the largest Italian organic certification body concerning the records of the inspection made over the period 2007-2009. The dataset contains structural and managerial data for the certified farms, and the outcomes of the inspection visits, in terms of types and number of sanctions issued for each inspected farm. Sanctions for non-compliance are classified as slight or severe, respectively referring to formal-bureaucratic noncompliance, and to more important violation of the disciplinary. Our aim is to analyse the relationship between the type of sanctions a farm receives, and the farm's structure and productions, aiming at the definition of potential risk factors. Two distinct models are considered, respectively for slight and severe sanctions. Given the large share of farms with zero sanctions, we apply zero inflated Poisson models to farm-level panel data. Results show that there is evidence of the role of co-dependence effects between the two types of sanctions in predicting the risk of non-compliances. Other common risk factors for both types of sanctions are grapes and livestock production. Specific factors increasing the risk of non-compliance are also found for slight sanctions (dry pulses, root crops, farm size and processing) and severe sanctions (cereals), while fruit and olives production reduce the risk on slight and severe sanctions respectively.

1. Introduction

The organic sector in Europe now involves more than 250,000 producers, of which 208,000 are located within the European Union (EU) (FIBL, 2011). Italy is one of the leading countries in the EU organic sector: it has the largest number of organic farms, while in terms of organic land area, it is second only to Spain. The organic sector in Italy has also grown rapidly in recent years. The certified land area increased from less than 200,000 ha in 1995 to nearly 1 million ha in 2009, while the number of operators in 2009 was just over 48,000.(1)

Certification procedures are a key feature of organic farming systems today, because only certified organic products can be labelled as such, thereby gaining access to the organic market and selling at premium prices.(2) However, the costs of the certification system are mainly borne by the organic farmers and processors, and therefore this can reduce the relative competitiveness of organic farming. A more efficient certification system would contribute to a significant reduction in the costs in the organic supply chain, and hence positively impact on the consumption of organic food while maintaining the benefits of trusted organic labelling.

The organic certification system is essentially based on inspections that are carried out by independent bodies (third-party certification), in accordance with the standards laid down by EU Regulation (EC) 834/07. This Regulation provides general guidelines for control visits and inspections, which should be based on risk assessments for non-compliance. A risk-based inspection approach would assist the control bodies, allowing them to plan better-targeted, unannounced inspections, and hence this would contribute to a more cost-effective system. While the potential for a risk-based inspection system in organic certification has been recently discussed by stakeholders (see, for example, Zanoli,[3] Padel[4]), relatively few studies have analysed the functioning of the organic certification and inspection systems from an empirical point of view. Gambelli et al.[5] provided a methodological approach to risk analysis for organic certification. Gambelli and Solfanelli[6] developed and implemented a Bayesian network model for the evaluation of the risk of non-compliance of a group of Italian organic farms. De Gennaro and Roselli[7] analysed the organic certification system in Apulia in terms of its efficiency and effectiveness.

One aim of the present study was to initially identify farm-level structural and managerial factors that affect the probability of non-compliance of Italian organic farms.

This probability does not, however, fully encompass the risk that is associated to non-compliance. The magnitude of risk is related to the probability of non-compliance to occur, and also to the potential consequences that might derive from the non-compliance itself, for the organic sector, the consumer, and society as a whole. This general approach to risk evaluation is acknowledged in the European regulations relating to the food sector, where risk is defined as “a function of the probability of an adverse health effect and the severity of that effect, consequential to a hazard”.[1]

However, here we follow the more specific approach of Regulation (EC) 834/2007, which defines the organic production rules and uses the term ‘risk’ in the sense of the probability of not fulfilling the requirements laid down in these Regulations. This study therefore analyses the factors that have an impact on the probability of non-compliance, as a contribution for the definition of a risk-based inspection system in the organic sector.

The structure of this paper is as follows. The data are described in section 2, while the count-data models used for the analysis are discussed in section 3. The results are presented in

[1] See Article 3(9) of EU Regulation 178/2002.

section 4, and discussed in section 5. The paper is then completed with the general conclusions on the factors that explain the probability of non-compliance in Italian organic farms, as well as with some policy recommendations.

2. The data

The data were provided by the Ethical and Environmental Certification Institute (ICEA)[2], as an abridged and anonymized version of their database on inspections and controls on the organic operators. In this report, we refer only to the farm-level panel data that consist of 25,600 observations (the ICEA 'universe') for the 2007-2009 period (see Table I).[3]

The dataset represents about 20% of the total Italian organic farms; with the remaining organic farms certified by other control bodies.[4] The data are evenly distributed over the country, with 37% of the farms located in the southern regions of Italy, 32% in the central regions, and the remaining 31% in the northern regions. The panel dataset is not balanced, with the participation pattern of farms across years shown in Table I (i.e. the number of the same farms included across the years). However, the panel dataset is sufficiently homogeneous, as 6,642 farms (64% of the sample) were included over all of the three years, and 1,873 farms (18%) were included for two consecutive years.

Table I. Farm participation patterns: number of the same farms across the years (2007-2009).

N° of farms	**2007**	**2008**	**2009**
6,642	√	√	√
1,238	√	√	×
799	×	×	√
751	√	×	×
635	×	√	√
132	√	×	√
114	×	√	×
Total Farms	**8,763**	**8,629**	**8,208**

[2]ICEA is among the oldest Italian certification bodies, it has the largest share of inspected farms, and it is one of the partners of the CERTCOST project.

[3] In total, inspection and control data for 29,481 farms were included, although data cleaning processes was necessary to purge missing information.

[4] Currently, in Italy, there are 16 authorised control bodies, three of which are only allowed to operate in the Bozen province.

The dataset contains basically three types of information: firstly, structural data such as farm size, type of crops and of livestock production; secondly, managerial data such as the availability of a license to sell organic products, farmer's experience as organic, presence of conventional land, processing activity; finally, data on sanctions imposed on the farms according to the results of inspections. The average number of inspections per farm was 1.49 per year, and these are divided according to annual inspections (1.35 per year), follow-up inspections (0.05 per year), and unannounced inspections (0.09 per year). The inspections labelled as annual are on average more than 1 per farm/year (which is the mandatory requirement in the EU Regulation), as the farms might have been visited one time for each operation (i.e. crop production, animal production and processing).

As ICEA did not record any detailed information on non-compliance, we have used the number of sanctions imposed on an operator after the inspections as a proxy for non-compliance. In other words, we assumed that non-compliance was followed by sanctions, at the appropriate level of severity. Regulation (EC) 834/07 classifies non-compliance as *irregularities* or *infringements*, and it is made clear that the former are less severe than the latter, although no explicit definitions are provided.

Noncompliance, once detected, is followed by the appropriate sanction, which is issued by the control body itself for all types of sanction[5]. The Accredia[6] guidelines[(8)] define five types of sanctions that are ranked according to their severity, ranging from warnings to exclusion from the organic sector.[7] In the guidelines, there is a strict correlation between non-compliance and sanctions, which means that a severe sanction is issued when a severe non-compliance is detected (aka, an infringement), and a less severe sanction is issued in response to a correspondingly less severe non-compliance (aka, an irregularity).

For simplicity, in our analysis, we have classified sanctions into two categories (see Table II): slight and severe. Slight non-compliance is associated with the sanctions of 'warning' (i.e. usually a simple letter with specific issues that need to be resolved before the next inspection, with no impact on certification) and 'intimation' (i.e. a more formal and ultimatum invitation to comply to resolve the detected issues, with no immediate impact on certification). Severe non-

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[5] This is not true in all EU countries, as the most severe sanctions in some cases are imposed by the Government.

[6] Accredia is the national authority for accreditation of certification bodies.

[7] An additional sanction category "exclusion for not paying the inspection fees" is reported in the guidelines, but this is not considered in the present analysis, as it is not related to non-compliance.

compliance includes the sanctions of 'suppression' (i.e. exclusion of the specific product or lot from organic certification), 'suspension' (i.e. temporary exclusion of the whole farm production from certification) and 'exclusion' (i.e. permanent exclusion of the farm and its productions from organic certification). Slight sanctions correspond to irregularities that mainly arise from the 'documental area' of the controls, e.g. missing or incomplete registrations, errors in the farm document archiving, lack of response to the control body requests, and/or missing mandatory documentation. Severe sanctions correspond to infringements, such as incorrect product identification and labelling, use of non-permitted substances, and/or cultivation of 'parallel' organic and conventional crops (e.g. organic and conventional wheat grown on the same farm in the same year). Furthermore, severe sanctions can be issued when the problems indicated in a slight sanction have not been correctly tackled and resolved by the farmer.

Table II. Classification of the sanctions.

Sanction imposed	Description of sanction effects	Sanction classification
Warning	Does not invalidate organic certification.	Slight
Intimation	Does not invalidate organic certification, but non-compliance must be solved within a specific time period established by the control body.	
Suppression	Implies the prohibition to sell as organic the product for which the non-compliance has been detected.	Severe
Suspension	Implies the prohibition to sell any of the farm products as organic. This is addressed to non-compliance that is considered as essential but with reversible effects.	
Exclusion	Implies certification withdrawal. This is addressed to the operator as a result of non-compliance that was detected as essential and with irreversible effects.	

The frequencies of various sanction types in absolute values are shown in Table III. The share of slight sanctions decreases significantly over the three years considered: from 11.78% in 2007, to 7.05% in 2009. On the other hand, for the same period, the share of severe sanctions shows a slight increase, from 1.55% in 2007, to 2.62% in 2009. In all three of the years studied, the number of slight sanctions was a lot higher than the number of severe sanctions, as infringements generally occur less frequently than irregularities. Over the three years covered by the analysis, there was a considerably high proportion of cases with zero sanctions, ranging between 88.22% and 98.45%, for slight and severe sanctions, respectively.

Table III. Frequencies of sanction occurrence by type and year.

No of sanctions per farm	Slight Sanctions			Severe Sanctions		
	2007	2008	2009	2007	2008	2009
0	8,024	8,082	7,778	8,665	8,436	8,034
1	494	407	302	67	142	142
2	216	116	113	26	46	24
3	11	13	9	3	4	7
4	17	10	6	2	1	1
5	1	0	0	0	0	0
6	0	1	0	0	0	0
Total farms	8,763	8,629	8,208	8,763	8,629	8,208
Total sanctions	1,032	724	579	136	250	215
(%)	11.78	8.39	7.05	1.55	2.90	2.62

In the present study, we are interested in factors that can impact on the likelihood of an operator to get a slight and/or severe sanction. Therefore, the data on the sanctions was analysed according to a set of potentially relevant risk factors (taken from the variables available in the dataset), which we have classified as farm structural and managerial risk factors, and crop/ livestock-specific risk factors (see Table IV).

Table IV. Variables (risk factors) included in the models.

Variables	Code and description
Type of sanction	
Severe sanction	= 1 if severe sanction was imposed on an operator; = 0 otherwise
Slight sanction	= 1 if slight sanction was imposed on an operator; = 0 otherwise
Managerial factors	
Conventional area	= 1 if the farm has conventional area; = 0 otherwise
Complexity of crop production	Crop Shannon index
Complexity of livestock production	Livestock Shannon index
Licence	= 1 if the farm is licenced to sell products as organic; = 0 otherwise
On-farm processing	= 1 if there are on-farm processing operations; = 0 otherwise
Organic experience	= 1 if the experience in organic farming is >9 years; = 0 if the experience <≤9 years
Structural Factors	
Cattle	= 1 if the farm has cattle; 0 = otherwise
Cereals	= 1 if cereals are cultivated; 0 = otherwise
Citrus	= 1 if citrus are cultivated; 0 = otherwise
Dry pulses	= 1 if dry pulses are cultivated; 0 = otherwise
Fallow	= 1 if fallow is present; 0 = otherwise
Farm size	Total agricultural area (km^2)
Fruit	= 1 if fruit are cultivated; 0 = otherwise
Goats	= 1 if the farm has goats; 0 = otherwise
Grapes	= 1 if grapes are cultivated; 0 = otherwise
Grasslands	= 1 if grasslands are present; 0 = otherwise
Green Fodder	= 1 if green fodder is cultivated; 0 = otherwise
Green Manure	= 1 if green manure is produced; 0 = otherwise
Industrial Crops	= 1 if industrial crops are cultivated; 0 = otherwise
Olives	= 1 if olives are cultivated; 0 = otherwise
Pigs	= 1 if the farm has pigs; 0 = otherwise
Poultry	= 1 if the farm has poultry; 0 = otherwise
Root Crops	= 1 if root crops are cultivated; 0 = otherwise
Sheep	= 1 if the farm has sheep; 0 = otherwise
Vegetables	= 1 if vegetables are cultivated; 0 = otherwise

For the potential risk factors, we formulated the following hypotheses:

H1: Slight and Severe non-compliance are co-dependent.

The small time dimension of our panel dataset does not allow an investigation of the effects of farmer fraud behaviour in the past. However, given that a farmer can be sanctioned in the same year for different non-compliance, both slight and severe, we can analyse if the two types of non-compliance are interrelated. Severe and slight sanctions detected within the same year are used in the slight sanctions and severe sanctions models, respectively. Dummies for both slight and severe sanctions were considered.

H2: Farmers who sell their products on the organic market, where they are paid premium prices, have greater incentive to non-compliance than those who just limit themselves to receive organic area subsidies and then sell their products on the conventional market. At the same time, licenced farmers might face more bureaucracy, and thus might be more likely to be non-compliant.

In Italy, to sell your products as organic, a special 'licence' is required from the control body, which issues specific authorization that identifies each lot produced/ processed and shipped. In our dataset, only 40% of the farmers had a licence to sell organic products.

H3: Larger farms are more likely to be non-compliant.

Control bodies consider farm size (total land area) as a risk factor for non-compliance, as this makes non-compliance more rewarding (the values at stake are higher: i.e. fraudster economies of scale).

H4: The risk of non-compliance increases with farm management complexity.

A farm with a complex crop rotation, and/or different parallel livestock productions could more likely be noncompliant due to managerial errors and/or difficulties in matching the organic standards for all products.

A measure of farm (management) complexity can be approximated by the number of crops or livestock types on a farm. A Shannon Index was used to measure the structure complexity of both the crops and livestock. The Shannon Index calculations referred to the EUROSTAT-coded crop and livestock categories used for the analysis.

The Shannon index[9] for each crop c_i or livestock species l_i was computed as follows:

$$Crops-Shannon = -\sum_{i=1}^{k}(c_i \ln c_i) \tag{1}$$

$$Livestock-Shannon = -\sum_{i=1}^{n}(l_i \ln l_i) \tag{2}$$

The occurrence of on-farm processing activities is also connected with H4. On-farm processing activities increase the farm complexity, and might increase the risk of non-compliance. Almost 17% of the farmers in the sample had processing activities in addition to their standard farming activities.

H5: Farms that have both organic and non-organic operations are more likely to be non-compliant.

According to EC Regulation 834/07, if a farm is not fully organically managed, then the risk of the co-mingling of organic and non-organic operations might increase. Therefore, farms with conventional land might be more likely to get sanctions. Almost 10% of the farms in the dataset had conventional land.

H6: The farmer 'organic experience', i.e. the number of years the farm has been organically managed, should reduce the risk of non-compliance .

The number of years a farmer has been certified by ICEA was taken as a proxy here, as the information on the actual number of years a farm was organically managed was not available. This variable therefore might underestimate the actual experience, as it does not consider possible years of certification with different control bodies in the past, or even periods of organic management before the EU organic Regulation was introduced.

Apart from these six hypotheses, we examined whether any specific crop or livestock increased (or decreased) the risk of non-compliance. This part of the analysis resembled more a data mining exercise than theory-based empirical testing. However, we felt that this information might be useful, to uncover latent risk factors that can be used to plan risk-based inspections in the future.

For the specific risk factors related to crops and livestock, the information was standardised using the EUROSTAT classifications. Thirteen categories of crop types were considered as dummies in the model. The crop categories were: arable crops (*cereals, industrial crops, dry pulses, root crops*), fodder crops (*grasslands, green fodder*), permanent crops (*olives, grapes, fruit, citrus*), *vegetables*, and unused land (*green manure, fallow*). Using these explanatory variables, we wanted to test some of the assumptions of risks as reported by the Accredia guidelines (e.g. that fruit and vegetables on an organic farm increase the probability of non-compliance). For the livestock types, five main categories were considered as dummies in the model: *cattle, pigs, sheep, goats and poultry*. The presence of crops and livestock types on the farms was measured with the dummy variables (see Table IV).

3. Model specification

Count data are specific cases of discrete data where the dependent variable takes only the integer non-negative values that arise from counting, rather than ranking. The data on the sanctions imposed on a farm as a consequence of the detection of non-compliance are the count data. The statistical treatment of count data is different from that of binary data or multiple-choice models, where the observations can take only two, or at least only a few, values. Linear regression models have frequently been used to count outcomes; however, there are several serious problems in the estimation of event-count data models with standard least squares.[10, 11] For this reason, statistical methods specifically designed for count data, such as Poisson and negative binomial regression models, might be more appropriate for the study.

However, in the case where the event counts are characterized by a large number of zero observations, the traditional application of a Poisson or negative binomial model might not be accurate. In our case, we observe an excess of zeros in the data (see Table III), that may be due to two reasons. On the one hand, we assume that most of the organic farmers are normally complying with the organic regulations, and that non-compliance is due to opportunistic behaviours, aiming at immediate practical advantages, though improper or forbidden. On the other hand, in any inspection system, the risk of potential 'under-reporting' of non-compliance/ sanctions is part of the problem. While the risk of 'false-positive' non-compliance is actually not relevant here (even in the case of product samples taken and tested for non-permitted substances, there is always a second testing procedure before the sanctions are imposed), the risk of 'false-negative' non-compliance is intrinsically related to any inspection procedure. Therefore, we expect that the level of detected non-compliance is lower than the actual non-compliance; e.g. as far as we know, in everyday life, we do not have to pay a fine every time we ever exceed a speed limit.

We have no information in our dataset relating to factors that concern under-reporting. However, a panel specification of the model allows the heterogeneity due to potential under-reporting to be considered in the individual random effects. Panel models allow general types of individual heterogeneity.[12, 13] Panel estimators can provide estimates that do not suffer from the inconsistencies due to latent individual effects. In a cross-sectional model, while estimating the relationships between the number of sanctions and the variables that represent the potential risk-factors, the only way to control for heterogeneity might be for the inclusion of other farm-specific variables. If there is not sufficient data that refer to such farm-specific variables that can lead to heterogeneity, individual effects remain unmeasured and pass into the error term as latent individual effects, which can produce inconsistent estimates in cross-sectional modelling. Instead, panel data models can be specified that follow the standard distinction between random-effects and fixed-effects approaches. Random-effects models assume that the individual effects follow a stochastic process, which might be a consistent specification for the handling of the issue of potential under-reporting. However, random effects require independency between the individual effects and the regressors; fixed-effects models relax this assumption, at the cost of a lower efficiency and of the impossibility to obtain an estimation of the time invariant regression coefficients (see, among others, Hsiao;[14] Baltagi[15]).

To handle count data with excess zeroes, in a study on defects in manufacturing, Lambert[16] proposed a technique called zero-inflated Poisson (ZIP) regression. A number of other studies, such as Mullahy,[17] Long[18] and Greene,[19] concluded that ZIP, or negative binomial regression, represents a practical way to model count data with excess zeroes. The zero-inflated model assumes a two-fold generation process for data: a zero-state process, where only zeroes are expected, and a count-state process where count data (including some zeroes) are expected. If the heterogeneity effects due to the potential underestimation of sanction occurrence is captured in the individual effect, the zero-state can therefore refer to the normally compliant organic farmers, who will be non-compliant only out of error. The count-state then refers to the organic farmers, who consider non-compliance as an option where there should be positive expected net benefits from their non-compliant, opportunistic behaviour. In other words, in a ZIP model, the expected number of sanctions for the zero-state process is $Y_{it} = 0$, with a probability p_{it}, while the expected number of sanctions for the count-state process is $Y_{it} = j$, with a Poisson distribution and a probability $1-p_{it}$. The probabilities of the possible outcomes are:

$$\text{Prob}\ (Y_{it} = 0) = p_{it} + (1- p_{it})R_{it}(0)$$

$$\text{Prob}\ (Y_{it} = \text{j}) = 1- (1- p_{it})R_{it}(\text{j})$$

where:

R_{it}(j) is the Poisson probability = $e^{-\lambda it}\lambda_{it}^{yit} / y_{it}!$;

λ_{it}= exp($\boldsymbol{\beta}_i$'$\mathbf{x}_{it}$), where $\mathbf{x}_{it}$ is the set of variables that explains the count-state regime (including individual random effects);

p_{it} is a logistic distribution, such that p_{it} = exp(γ'$\mathbf{z}_{it}$)/[1+ exp(γ'$\mathbf{z}_{it}$)], where $\mathbf{z}_{it}$ is the set of variables that explains the zero-state regime.

The Poisson is a parsimonious count-model formulation, as it imposes the condition that the mean and variance of the process are the same (equidispersion). Other count distributions can be considered, like negative binomial and gamma distributions (see, among others, Cameron and Trivedi[12, 20, 21]; Boucher et al.[22]), which allow for a more general formulation of the dispersion, at the cost of higher numbers of parameters that need to be estimated. In panel random-effects models in particular, a negative binomial of gamma specification for the count state might over-parameterise the model. Indeed, the random-effects estimator actually adds a heterogeneity term to the standard Poisson specification - the individual random effect.[23]

Given these considerations, we used a random-effects panel estimator based on ZIP specification. Two distinct models were considered: one for the slight sanctions, and one for the severe sanctions. The zero-count regime is modelled using the following variables: longer than 10 years organic experience of a farmer, the occurrence of other sanctions (slight sanctions for the severe sanction model, and *vice versa*), and farms with conventional (non-organic) land. Limited farmer experience could be a proxy for the adoption of organic practices at the turn of the century, the years when organic farming in Italy experienced particularly favourable market and policy conditions that might have attracted more opportunistic farmers. Information or data concerning individual farmer-specific attitudes to fraud are not included in the data; we only have information about the behaviour of a farmer, i.e. if she has committed any type of non-compliance. We thus used the occurrence of other sanctions as a proxy for the attitude of a farmer to non-compliance. Finally, if a farm is not totally converted to organic (and therefore still has conventional land use) this might be another indicator of the opportunistic behaviour of a farmer. The rest of the risk factors discussed in the previous section are used as explanatory variables for the count regime of the ZIP model.

4. Results

A testing procedure was followed to check on the critical steps in the estimation (Table V). First, we performed a test to determine the statistical significance of individual effects, the results of which indicate the preference for the use of a panel estimator.

A Hausman test for the choice between random-effects and fixed-effects panel specifications was performed. However, in our dataset (based mainly on dummy variables for crops and livestock), within-individual variation is extremely low, and near to zero for most of the explanatory variables, as most of these are structural variables, which have very low variation across the limited time span of our database. The fixed-effect approach in our case cannot, therefore, be considered as a feasible option. Indeed, the Hausman test computation fails, due to the extremely low within-individual variability for most of the explanatory variables, which causes singularity in the covariance matrix of the fixed-effects estimator. Under such conditions, the choice of the random-effects option cannot be rejected;[25] a random-effects formulation is also consistent with our requirement for the handling of heterogeneity due to potential latent under-reporting effects, which are likely to be randomly distributed across individuals.

As mentioned in the previous section, the Poisson specification requires equidispersion (equal mean and variance): we could not perform the standard testing based on the comparison between Poisson and negative binomial models,[26] as the latter could not be estimated, due to overparameterisation of the random-effects ZIP model (see section 3 for details). The performance of the ZIP model with respect to standard Poisson specification has been considered by the comparison of both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which can be considered as a feasible solution when comparing non-nested models, as in our case (see, for example, Anderson;[28] Boucher et al.,[22] for an application to count *vs*. zero-inflated models). Also, a Vuong test[8] was performed, for a comparison of the ZIP *versus* standard Poisson model, and the results support the choice of the ZIP model.

Table V presents the results of the ZIP regression panel data model for both slight and severe sanctions. The zero-state part of the model, specified as a Logit process, estimates the coefficients of the actors used to discriminate between the two regimes. A positive and significant

[8] See chapter 25 in Greene[26] for more details on the Vuong statistic used for testing non-nested models.

coefficient indicates that the respective variable increases the probability of a farm belonging to the zero state. The effects of the occurrence of other sanctions is significant and negative for both models,. Conventional land has significant coefficients for both the slight and severe sanctions models, although with opposite signs. In the slight sanction model, farms with conventional land are more likely to belong to the zero state, which is counter-intuitive. In the severe sanction model, farms with conventional land are less likely to belong to the zero state, as theoretically expected.

Finally, the organic experience of the farmer is significant only in the severe sanctions model, and the sign of the coefficient fulfils the theoretical expectations: farmers that have been certified for at least 10 years are more likely to be in the zero-state group. In contrast, in the slight sanction model, this variable does not contribute towards any prediction of either of the two states.

The count-state part of the model, which is specified as a Poisson process, estimates the coefficients for the factors that influence the number of detected sanctions by the control body during the inspection. Here, a positive and significant coefficient indicates that the respective risk factor increases the probability that a farm has a higher number of sanctions. The coefficients referring to *grapes, grasslands*, *cattle* and *poultry* show positive and statistically significant coefficients for both the slight and severe sanctions models. *Cereals* and *pigs* increase the probability of severe sanctions, while *farm size*, *on-farm processing*, *root crops, green fodder* and *dry pulses* increase the probability of slight sanctions. Negative effects on sanction probabilities were only found for *fruit* in the slight sanction model, and *olives* in the severe sanction model.

Table V. Results of the Zero-Inflated Poisson models for slight sanctions and severe sanctions.

Variable (Risk factor)	Coefficient: Slight sanctions	Coefficient: Severe sanctions
Zero-count (logit) regime		
Conventional area	**0.72362857***	**-0.68300107***
Organic experience	0.08856185	**0.32120589**
Severe sanctions	**-0.47064064***	-
Slight sanctions	-	**-0.40674891***
Constant	**.86904743***	**2.51739201***
Poisson-count regime		
Cattle	**0.63029210***	**0.56358781**
Cereals	-0.08505534	**0.67003519***
Citrus	0.00625110	0.16882903
Complexity of crop production	0.13706860	0.02033748
Complexity of livestock production	-0.35852074	-0.55898482
Dry pulses	**0.24686992***	0.17904731
Fallow	0.06123420	0.13430100
Farm size	**0.06327743***	0.03004482
Fruit	**-0.33090595***	-0.21826444
Goats	0.18470816	-0.09234492
Grapes	**0.31004147***	**0.50096075***
Grasslands	**0.44784066***	**0.33792005**
Green fodder	**0.25491331***	0.23546017
Green manure	0.07100406	0.11021614
Industrial crops	-0.02446424	0.18836969
Licence	0.04596450	0.11757959
Olives	0.03837277	**-0.44052393***
On-farm processing	**0.48178438***	0.45950137
Pigs	-0.12815705	**0.65817623**
Poultry	**0.35142671***	**0.80354488***
Root crops	**0.27192486***	-0.35106104
Sheep	0.82248706	0.18849671
Vegetables	0.05741346	0.33845876
Constant	**-2.04668225***	**-2.04715646***
Obs. Number	25.600	25.600
AIC ZIP	0.56689	0.19598
AIC Poisson	0.57701	0.20206
BIC ZIP	0.57612	0.20521
BIC Poisson	0.58593	0.21065
Lr Test Panel *vs.* Pooled prob ≥chibar2	0.000	0.000
Vuong test ZIP vs Poisson	-65.96	-17.69

Zero-count regime: positive coefficients refer to risk factors increasing the probability of a farm to belong to the zero state (i.e. compliant farmer); Poisson-count regime: positive coefficients refers to risk factors increasing the probability of non-compliance.
Levels of significance: * p <0.05; ** p <0.01; *** p <0.001

5. Discussion

The data presented in the previous section relate the probability of non-compliance (*rectius* sanction) to a number of structural and managerial risk factors, such as specific crops and livestock production. These data need to be interpreted with caution to avoid inappropriate simplifications.

Only a subset of the common risk factors is found in both the slight sanction and the severe sanction models. Such a result is relevant, as it shows that a general risk evaluation for non-compliance considered with no distinction between slight and severe sanctions, could be partial or misleading. In the zero-state part of the model, this aspect is well illustrated by the contrasting results in terms of the conventional land coefficients. The coefficient of conventional land in the slight sanctions model shows a rather counter-intuitive sign, as we expected that farmers with conventional land might show higher risks of non-compliance.

To discuss the results of the whole model (both the zero-state and Poisson-state parts), we have taken the Accredia RT16 guidelines[8] as a benchmark. In these guidelines, this Italian accreditation authority establishes a framework for the attribution of a risk rating to each farm. This risk rating, which ranges from 1 to 3, is based on a number of variables (risk factors) and is used to determine the number of visits that each farm will be subjected to (including the mandatory annual inspection). Our data are partially consistent with the indications of Accredia.[8]

On the one hand, among those factors that appear as relevant in both of the sanctions models, livestock, grapes, and occurrence of previous/ other sanctions are coherent with the framework of the Accredia guidelines. The picture that emerges from our analysis is that cattle and monogastrics (pigs and poultry) increase the risk of sanctions (pigs are only significant in the severe sanction model). In general, livestock operations appear to be associated with greater risk. Indeed, farms with dry pulses, grassland, green fodder and root crops, which are often part of the rotation scheme of farms with animal production, are more likely to have slight sanctions.

On the other hand, cereals and grassland are not considered as risk crops by Accredia. As 32% of the farms produced cereals (as the average over the 3 years), it is probably a very general factor. However, as it is significant for severe sanctions, coupled with grassland, it might simply confirm the higher risk of certain kinds of livestock operations: cereals enter as animal feed in the diet of cattle and monogastrics, and in organic farms a high proportion of this feed needs to be produced on-farm.

Farm size appears as a risk factor in both the Accredia guidelines and in our data, at least with respect to irregularities: larger farms are more likely to commit slight non-compliance.

Fruit production does not emerge in our analysis as a relevant risk factor for severe sanctions, and it is even negatively correlated with the probability of slight sanctions. This result is in contrast to the indications of Accredia, where all fruit operations are considered to be associated with increased risk.[8] In our analysis only grapes, rather than all fruit, are a risk-associated crops. Citrus fruit are also non-significant for predicting risk. Our data provide a more detailed picture than the Accredia *a-priori*, rule-based approach.

Finally, farmers who have a licence to sell organic products are included by Accredia as the maximum risk operators. Our evidence contradicts this risk hypothesis, although the approach used by Accredia for the definition of this risk factor is not simply related to the probability of the occurrence of non-compliance, but also to the impact that a non-compliant licenced farmer would have on the organic market.

In summary, our results do not confirm hypothesis H2. For the other hypotheses, we see only partial confirmation for hypothesis H4 (on-farm processing is significant in the prediction of the risk of slight sanctions) and hypothesis H5 (non-organic operations appear to increase the risk of severe non-compliance only). From our dataset, hypotheses H1, H3 and H6 appear to hold up to empirical verification.

6. Conclusions

A first result that has emerged from our analysis is that slight and severe sanctions are associated to different risk patterns. A lack of discrimination between these two types of sanctions might thus lead to inappropriate modelling and misleading results. This should be considered when planning risk-based inspections, as the Accredia guidelines are designed to do.

Another important consequence of our findings is that based on these currently available data, a risk-based inspection strategy will be relatively difficult to implement. The inspection data mainly contain data on the structural aspects of the farms, and to a varying degree, some data on the quality/ quantity of the farm management; however, they contain little or no personal information about the farm operators, the farmers themselves. Indeed, the data collected by the control bodies (i.e. not only by ICEA) are particularly detailed with respect to the structural aspects of the farms. For example, they include very detailed crop classifications, with very little information on the farms/ processors (e.g. age of farmer/ processor, when it is a family enterprise, their total turnover, their liabilities and debt, their solvency). In our analysis here, we were obliged to use proxies to model the attitudes towards non-compliance, such as the occurrence of other sanctions, the organic experience of the farmers, and the existence of non-organic land on the organic farms.

Similarly, while using models based on evidence of non-compliance– as we have used here – can help in the limiting of what we know already about risk, this cannot avoid unpredictable (and potentially disruptive) events based on 'new', yet-to-be-discovered factors. This is the well-known problem of induction, which was originally proposed by the philosopher David Hume[(29)]. We can rephrase his thoughts in the following way:

> 'No amount of observations of compliant farmers can allow the inference that all similar farmers are compliant, but the observation of a single non-compliant farmer is sufficient to refute the conclusion'

Furthermore, as we cannot infer our immortality from the simple observation that we have not died yet, we cannot rule out the possibility that an up-to-now compliant operator will breach the rules tomorrow; we can only determine which factors will increase this risk, based on what we know already.

We also cannot rule out that in the future new risk factors will emerge, although we can at least insure ourselves against this asymmetry of information (regarding the future) by a consideration of which type of non-compliant behaviour will have the greatest effects on the market and on consumer safety and confidence[(30)]. An efficient risk-based inspection system, therefore, should weight up the known probability of occurrence of a given non-compliance according to the severity of its impact (and, possibly, according to the probability of detection of the given non-compliance, which is very difficult to assess). Indeed, a risk-based system that produces risk ratings is applied by bankers for loan evaluations, and by insurers for fixing insurance premiums. Similarly, in production engineering, risk ratings form the basis of the well-known Failure Mode Effect Analysis,[(31)] to assist the foolproofing of a process or a design. We thus believe that an efficient and effective inspection system in organic farming should be more explicitly modelled according to such risk-based approaches.

Acknowledgments

This study was funded as part of the CERTCOST Project, agreement no. 207727 (http://www.certcost.org), with financial support from the European Community under the 7th Framework Programme. This paper reflects the views of the author(s) and not those of the European Community, who is not to be held liable for any use that may be made of the information contained.

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