Zanoli, Raffaele; Gambelli, Danilo; Solfanelli, Francesco and Padel, Susanne (2014) Assessing the risk of non-compliance in UK organic agriculture: An econometric analysis. British Food Journal, 116 (8), pp. 1369-1382.

1. Introduction

The competitiveness of organic farming depends on products' diversification and quality in comparison with conventional farming. Certification is a crucial element in the organic system to assure and maintain the required standards for organic production, and to guarantee the quality of organic products to consumers. In the European Union certification through an accredited body is required by Regulation (EC) No 834/2007 (EC 2007). Through direct and indirect costs of certification procedure affects relative profitability of organic operators (Stolze, 2012). A more efficient certification system may contribute to reduce transaction costs (Zorn et al., 2012), and to increase organic system competitiveness while still maintaining the benefits of trustworthy organic labelling. This goal can be achieved by developing a cost-effective inspection programme that provides assurance of acceptable integrity and reliability, hence shifting the organic certification system more towards a risk based strategy. Risk-based inspections systems use the findings from a formal risk analysis – according to defined criteria – to guide the direction and emphasis of the inspection planning and the physical inspection procedures. The potentials for a risk-based inspection system in organic certification have been recently discussed in Padel (2010) and Dabbert (2012). In the context of a risk-based inspection system, the evaluation of risk is directly dependent on the definition of risk that is assumed. Two regulations can be considered for what concerns the definition of the risk of non-compliance. The European food law laying down general principles and requirements of food law defines risk as "a function of the probability of an adverse health effect and the severity of that effect, consequential to a hazard" (Art 3(9) of Regulation (EC) No 178/2002) (EC, 2002). A more specific reference to risk (Regulation (EC) No 834/2007) (EC, 2007) refers to the probability that non-compliance with the organic regulation occurs, irrespective of the magnitude of the direct social damage potentially associated with it. In this paper we have considered the latter definition. See van Asselt et al. (2012) for a discussion on methodological aspects of risk-based controls in the food sector, and Hutter and Amodu (2008) for an analysis of risk management in food safety in UK. Gambelli et al. (2012) and Zorn et l. (2013), provide an analysis of the determinants of non-compliance respectively for the Italian and German organic sector.

The aim of this paper is to provide a risk-based analysis of non-compliance in the organic certification system in UK. We used a formal econometric model of risk analysis to provide empirical evidence on the determinants of non-compliance in organic farming. A panel of data from the archives of the largest control body in the UK for 2007 to 2009 is used, and specific analyses are performed for two types of non-compliances. A zero inflated count data model is used for the estimation, taking into account the fact that the occurrences of noncompliance are very sparse.

The structure of the paper is as follows: Section 2 provides a description of the organic certification system in the UK, Section 3 describes the data used for the analysis, Section 4 describe the model used for the analysis, Section 5 provides description and discussion of results, and Section 6 concludes the paper.

2. The organic certification system in the UK

Organic agriculture in the UK has long history, dating back to Lady Eve Balfour who founded the Soil Association in 1946 with the first standard published in 1967, their structure serving as an example for other standards, followed by a first governmental standards (UKORFS) published in 1987. The number of farms has increased from approximately 300 holdings in 1985 to nearly 5,000 by 2009. The UK is an important producer of organic in terms of land area (738,709 ha, 4,946 producers) and was in 2009 the third largest market in Europe terms of retail sales value after Germany and France (Willer and Kilcher, 2010). The largest land area is found in England (50.2%), followed by Scotland (33.8%) and Wales (14.3%), with the remainder in Northern Ireland (1.7%). Important land use categories are grassland, both temporary pasture/clover (17.2% of organic and in-conversion) and permanent pasture including rough grazing (67.1%), followed by cereals and other arable crops (9.6%) and fresh vegetable incl. potatoes (2.5%). Important species livestock are dairy cow, beef and sheep for meat production and poultry. In Table 1 these are shown compared to the annual June Survey of Agriculture data (DEFRA, 2012).

<Place Table 1 about here>

The UK has a system of accredited private organic certification bodies which are overseen in their activities by the Organic Farming Branch of the Department for the Environment, Food and Rural Affairs in England (DEFRA) fulfilling the legislative function of the Competent Authority for the whole of the UK. DEFRA is assisted by the by the UK Accreditation Service UKAS that also accredits the control bodies according to European Norm EN 45011.

In 2009, nine control bodies were registered in the UK (EC, 2012, two of which are Irish bodies operating only in Northern Ireland[1].

The Soil Association is the largest control body operating a private standard that is different from the Regulation (EC) No 834/2007 (EC, 2007) for organic food. According to information provided by the organisation, the Soil Associations Standards exceed the EU Regulation especially in areas concerning the environment and animal welfare and includes standards for areas not covered by government or EU regulations, such as conservation, textiles and health and beauty care products[2]. The organic rules database lists 61 differences between the previous Regulation (EEC) No 2091/91 (EEC, 1991) and the Soil Association standard based on a detailed comparison of the standards carried out in 2005 (see Schmidt et al. 2007 for details of the comparison). The differences relate to various aspects of livestock production, on farm biodiversity and conservation, use of fertilisers and other inputs and horticultural crops[3]. The Soil Association certified about 48% of all producers and 72% of all 1,798 organic processors in the UK in 2009 (unpublished information provided by DEFRA).

3. Data description

The data used in this research have been extracted from an anonymized version of the archives of Soil Association[4] on inspections and controls on organic operators licensed with them. The dataset consists of a panel of 5,912 observations referring to 2,346 farms observed over the 2007-2009 period and represents about 44% of total UK organic farms (Lampkin et al., 2011). The panel is unbalanced, i.e. not all the farms are recorded for the same number of years. However, it is quite homogeneous, as 1,516 farms (64.6% of the sample) were observed over all time periods and 518 farms (22.1% of the sample) were observed for two consecutive years. The data are

[1] These are Organic Farmers and Growers Ltd (OF&G-UK2), Scottish Organic Producer Association (SOPA-UK3, Scotland only), Organic Food Federation (OFF-UK4), Soil Association Certification Ltd (UK5), Bio-Dynamic Agriculture Association (BDAA -UK6), Quality Welsh Food Certification (QWFC, UK13, Wales only) and ASISCO (UK15).

[2] http://www.soilassociation.org/certification [accessed 20 March 2012]

[3] http://www.organicrules.org [accessed 20 March 2012]

[4] Soil Association Ltd. is the leading certifier of organic food in the UK and is one of the partners of the CERTCOST project.

collected by the control body for the purpose of client administration and to provide various statistical data to the competent authority. The dataset provides information at the farm level on structural-managerial characteristics and detected non-compliance. Inspection visits are distinguished into mandatory annual inspections, follow-up inspections in case of previous non-compliance, and unannounced inspections. Non-mandatory inspections are on average 5.8% of total inspections in the three years considered. Information about non-compliances originates from the inspectors report that is filled in during the visit by the inspector who can issue three categories of non-compliances (see Table 2). Information about the reasons causing the non-compliance was only available from a free text source and could not be used in the analysis. All cases of critical non-compliance are referred to the certification department, where decisions about manifest non-compliances and sanctions and/or termination of licences are taken. This information was not re-entered into the client database and could therefore not be used for this analysis.

The share of detected noncompliance over the number of controls are likely to change according to type of inspection. For what concern annual inspections, the share of noncompliance ranges from 42.1% for minor noncompliance to 8.8% for major noncompliance and 1.5% for critical noncompliance. When non mandatory inspections are considered (namely: follow up and unannounced inspections) the share of noncompliance ranges from 51.8% for minor noncompliance to 20.6% for major noncompliance and 8.9% for critical noncompliance. For both mandatory and non mandatory inspections the share of detected minor noncompliance is substantially higher than that referring to major and critical non compliances. However the difference between mandatory and non mandatory inspection in term of detected non compliance are remarkable, particularly for what concern major and critical noncompliance. These results show that non-mandatory inspections can be considered as a critical element of organic certification.[5] Planning of non-mandatory inspections could be established through a strict partnership between third party control bodies and group of farmers which implement Internal

5 This statistics should not be considered as representative of the organic sector in UK, since it's based on data from one control bodies operating in UK and represents therefore only a share of organic operators.

Control System (ICS). See Moschitz (2011) and Rehber (2011) for more details on the group certification and internal auditing system.

<Place Table 2 about here>

The frequencies of the different types of non-compliance are shown in Table 3. The share of compliant farmers is the highest: most farmers have no minor, major or critical non-compliance. For all the three years, the number of minor non-compliance was higher than the number of major non-compliance. The share of minor non-compliance is relatively stable across the three years, while the share of major non-compliance showed an increase from 5.8% in 2007 to 9.1% in 2009. Critical non-compliance is particularly sparse but shows a considerable increase in 2009. The number of non-compliant farms is negatively related to the number of non-compliances occurrence per year, i.e. farms with two or more non-compliance are less numerous. However about 46% and 24% of non-compliant farms have on average respectively more than one minor or major non-compliance.

<Place Table 3 about here>

Our aim is to explain the number of non-compliance occurring at the farm level using a set of risk factors, the choice of which was necessarily limited by data availability. The list of the potential risk factors we have taken into consideration is shown in Table 4. The dataset has been trimmed to eliminate observations with incomplete data (e.g. farms with no information on type of crop and livestock production) and two farm with abnormally large size (above 14,000 ha). When referring to dichotomous variables, the mean indicates the percentage of farms where that variable is present. The risk factors have been clustered into two groups: general risk factors, and managerial risk factors. General risk factors refers to non-compliance evidence, farm types, farm size, presence of conventional land and farm/farmer's experience as organic. We use data on non-compliance as a proxy for non-compliant attitude of farmers. Evidence of major and/or critical non-compliance is used to consider potential co-dependence effects on the risk of minor non-compliance (Model 1), and evidence of minor and/or critical non-compliance are used to consider potential co-dependence effects on the risk of major non-compliance (Model 2). Farm types dummies are included to discriminate the potential effects and differences due to the different categories of farms, and to take into account the structural differences in terms of risk of noncompliance that might be due to the general structure of the farms. Four farm types are considered: arable, livestock, horticulture and mixed. The arable farm type refers to farms where only arable crops are cultivated, with no livestock production and no fruit and horticulture production. The horticulture farm type refers to farms specialised in fruit, vegetables, glasshouse crops, herbs and aromatic plants, with no livestock and no arable crops productions. The livestock farm type include farms with livestock breeding (cattle, sheep, pigs, poultry). In this farm type farms with grassland and/or crop production (excluding horticulture) are also considered. Finally the mixed farm type includes farms with a mixture of crops and livestock, not classified in other farm type due to mixed status, e.g. a farm with a combination of livestock, arable and horticultural production[6]. Please note that each farm in our sample is univocally classified in one of the four farm types (i.e. the four farm types are mutually exclusive and orthogonal).

For what concerns the other general risk factors, we expect that the presence of conventional land in the farm is an indicator of a not complete involvement of the farmer in the organic approach. About 25% of the farms in our dataset have conventional land, and for these the average share of land managed organically is 72.3%. Finally we expect that farmers with less experience in organic farming might be more likely to commit errors or could be more likely driven by opportunistic motivations to farm organically. The variable "Farmers' experience as organic" should be considered as a proxy, since information on the actual number of years the farm has been managed organically was not available. This variable measures the number of years a farmer is certified by Soil Association, so it does ignore possible years of certification with different control bodies in the past. Furthermore, for most operators that registered with the Soil Association prior to May 1999 the same date was used when the electronic recording system was set up. Therefore this data underestimates actual farmers' experience, but is nevertheless used in the analysis to discriminate farmers who joined the certification body more recently from those who joined earlier. In fact, a farmer certified for a short period could be one newly converted or one changing certification body for some reason, possibly opportunistic: for the purpose of our risk analysis both options could be relevant. Finally, farm size can be considered a risk factor because a large farm could be more difficult to manage and because the potential benefits from opportunistic behaviours could be more rewarding when referring to large production sizes.

Crops and livestock types are taken into consideration to identify possible enterprises that could specifically increase the risk of non-compliance. A large share of farms have grassland, fodder, and cereals, which represent the core of the farming rotation and is comparable to the general organic sector in the UK (see above). The sample is strongly characterised by farms with livestock production and particularly by grazing livestock. Important livestock categories are cattle and sheep[7] (49.9% and 34.1% of farms with cattle and sheep respectively), followed by poultry (15.3% of the farms) and pigs (8.2% of the farms).

<Place Table 4 about here>

4. Model specification

A discrete count data model was used to measure the marginal contribution of each risk factor on the probability of a higher number of non-compliance occurrences. Standard count data models like Poisson or negative binomial models in our case are most likely mispecified since the large share of zeroes would violate the distributional requirements of those models. The reason for the large share of zeroes in non-compliance records could be due mainly to two reasons. The first one is that organic farmers are ethically involved and therefore “normally compliant”. Some studies concerning motivations to conversion in UK (Rigby et al., 2001; Padel 2001, 2008) show how personal motivations, like ethical, social and environmental concerns, play an important role in the decision for conversion. We therefore expect that as a general rule organic farmers tend to actively comply with the regulations, as indicated from data shown in Table 2. However, non-compliance can occur due to: a) managerial faults, e.g. due to lack of knowledge standards or to structural and managerial characteristics of the farm; b) intentional frauds due to opportunistic behaviours.

The second reason for zero inflation is due to the potential under-reporting of non-compliance. Necessarily, we only have records concerning non-compliance that is actually detected, but we

[7] Goats are grouped together with sheep. However farms with goats account for less than 1% of total farms in the sample.

have no idea about the number and kind of non-compliances that could escape the inspections. Reasons for potentially undetected non-compliances could be: the timing of the visit (e.g. a farmer could commit a non-compliance after the annual control visit), the effectiveness of the inspection visit, the percentage of (product/soil) samples taken, the number of unannounced visits, etc. We assume that the under-reporting effect is randomly distributed at the farmer-individual level. This issue addresses the fundamental statistical problem of underreporting in similar systems, which appears because not all non-compliances are detected and recorded in the data (Allingham and Sandmo, 1972; Feinstein, 1991; Sandmo, 2002, Winkelmann & Zimmermann, 1995; Winkelmann, 1996).

To solve the zero-inflation problem we use a zero-inflated Poisson (ZIP) model specification in a random-effect panel format. The under-reporting factor, which introduces individual heterogeneity in the model, is captured by the individual random effect of the panel model (Cameron et al., 1998; Boucher and Guillén, 2009). For details on zero-inflated count data models see, among others, Lambert (1992), Mullahy (1986) and Greene (1994, 2007, 2008). Zero-inflated models consider a twofold generation process for the dependent variable (i.e. the number of non-compliance): a zero-state process where only zeroes are expected, and a count data process where count data (including some zeroes) are expected. The zero-state process refers to "normally compliant" farmers, following a logit distribution. The non-zero, or count process measures non-compliance occurrence due to managerial or intentional faults, following a Poisson distribution. The Poisson distribution was preferred to other distributional alternatives for its parsimony in parameters, which prevents over-parameterisation problems that might arise in panel count models (Greene, 2007). The expected number of non-compliances for the zero-state process is $y_{it} = 0$ with a probability p_{it}, while the expected number of non-compliances for the count process is $y_{it} = j$, with a Poisson distribution and a probability $Prob\ Y_{it} = 1- p_{it}$.

The probabilities of the possible outcomes are:

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

(2) $Prob\ (Y_{it} = j > 0) = (1- p_{it})R_{it}(j)$

$R_{it}(y)$ is the Poisson probability $= e^{-\lambda it} \lambda_{it}^{\ yit} / y_{it}!$; $\lambda_{it} = exp(\beta' \boldsymbol{x}_{it})$, where x_{it} are the covariates of the count process;

p_{it} ~Logistic (v_{it}); $v_{it} = \gamma' \mathbf{z}_{it}$, where $\mathbf{z}_{it}$ are the covariates for the zero-state process.

The zero-state part of the models is explained by the general risk factors, that we expect to discriminate between compliant and non-compliant attitudes (Table 3). We consider the lack of non-compliance evidence and of conventional land, small size of the farms (UAA) and the length of the farmer's experience as organic, as indicators for "normally compliant" behaviours. We also include here three dummies for arable, livestock and mixed farm types (we exclude horticulture to avoid collinearity). The count process is explained by the set of structural and crops-livestock production risk factors (Table 3) that we expect may have an impact onto the likelihood of non-compliance occurrence. Given the general lack of information on these issues, this part of the analysis resembles more a data mining exercise than a theory-based empirical testing, particularly with regards to the different crop and livestock productions.

5. Results and discussion

Both Model 1 and Model 2 have been formalised on the basis of the following hypothesis: need for a panel model estimation due to the relevance of farmers specific individual effects; the individual effects are distributed randomly (Random-effect model specification); need for a zero-inflated count models due to the large share of zeroes in the dependent variables. Table 5 shows results for Model 1 and Model 2, and for the test of the hypothesis used for the models' specification. For both models, the LR test for panel vs. pooled models confirms the requirement for the panel specification. A Hausman test for random vs. fixed effects models could not be computed due to the extremely low time-variation of most of the explanatory variables, which causes singularity in the covariance matrix of the fixed effects estimator. However, under such conditions the choice of the random effect option cannot be rejected (Greene,2008). These results are relevant as in our model individual random effects are considered as a proxy for the underreporting effect of non-compliance. Finally the Vuong test for ZIP vs. standard Poisson model confirms the requirement for a zero-inflated Poisson specification for a better fit of the zero-biased distribution of the dependent variables.

The results of the estimated coefficients do not show risk-decreasing factors, and as a consequence, it is difficult to define specific low risk farm-types. Among the general risk factors used in the zero-state part of both Model 1 and Model 2, those referring to the co-dependence of non-compliance are found as statistically significant. The negative sign of the coefficients indicate that they negatively affect the probability of zero non-compliance. In other words, the occurrence of major and critical non-compliance increases the probability of occurrence of the minor one; similarly the probability of occurrence of major non-compliance increases when minor non-compliance occur. These results are consistent with those of Gambelli et al. (2012; 2012a, 2012b) and of Zorn et al. (2013). The relevance of co-dependence effects for non-compliance can be interpreted as the indirect measurement of the farmers' attitude to errors/fraud. Data on farmers' personal characteristics, bank information, the debt history of the operator and their solvency, their criminal record, etc., could provide more detailed information, and improve the predictive power of the model (Dabbert, 2012). The livestock farm type is the only one with a significant impact on the likelihood of non-compliance in Model 1. For what concerns the other general risk factors, neither the presence of conventional land nor the experience of the farmer as organic show relevant impact on the probability of non-compliance occurrence. The experience of the farmer was used to consider the idea that recently converted farmers are moved more by opportunistic motivation, and hence could more likely be non-compliant and may also make more mistakes due to lack of experience. No evidence for this hypothesis comes from our models, and this result is compatible with those of Padel (2008) who showed that "later" organic farmer are not ethically less involved than the earlier converted ones.

With reference to the count-regime part, the statistically significant risk factors in Model 1 are green fodder, root and industrial crops, and the livestock production in general that is confirmed as a critical risk factor. Green fodder, industrial crops and root crops are in fact indirectly related with livestock production as they can be used as animal feed. Furthermore, livestock production in general (cattle, sheep and poultry) is found as a relevant risk factor in the minor non-compliance model. Other reason to consider arable crops as a specific risk factor could be that non-compliances for operators growing arable crops are related to the use of non-organic seed or the use of restructured inputs that would required prior permission of the control body. Many non-compliance occur because operators use non-approved inputs because of an ignorance of specific rule. These results are partly confirmed in the count-regime part of Model 2, that shows pigs production and green fodder as risk factors significantly increasing the likelihood of a high number of non-compliance.

From the point of view of a risk-based model, the lack of relevance for some risk factors in both models can be considered a valuable information too. In particular specific production like fruit and vegetables as well as indicators for farm size and complexity do not have a significant impact on the risk of non-compliance.

<Place Table 5 about here>

6. Concluding remarks

The real causes of non-compliance are obviously latent, and the data available restricts our analysis to inferences referring to structural and managerial risk factors of a farm.

Our empirical findings show that the share of non-compliant farmers in UK is low, particularly for what concerns the most severe types of non-compliance. The main factors contributing to the risk of non-compliance are: livestock production (particularly pigs), crops related to livestock breeding, and other non-compliant behaviours (co-dependence).

Other risk factors like conventional area, and farmers' experience as organic, have not emerged as relevant. These results are consistent with those of the limited literature on this issue, and represent an important step towards a more formalised and structured approach to inspections procedures. However these results are based on analysis of available data, which are mainly referring to structural aspects. We think that structural data are probably not sufficient for in-depth risk-based modelling. An important share of the explanatory power of our models resides in behavioural factors represented by concurrent non-compliance, which behaves as a proxy of unmeasured farmers' personal information. Therefore, we argue that the availability of farmers' financial information like turnover or capital stock, and of data concerning the characteristics of the farmers, are likely to increase the ability of any model to predict the occurrence of non-compliance, especially the most severe type.

More in general, we conclude that shifting to risk-based inspections will uncontestably improve the effectiveness of organic certification, given the superior ability of probability-based models in spotting farmers with high risk of non-compliance over purely random or heuristic empirical methods.

References

Allingham, M. G. and Sandmo, A. (1972), "Income Tax Evasion: A Theoretical Analysis", *Journal of Public Economics*, Vol. 1, pp. 323–338.

Boucher, J.P. and Guillén, M. (2009) "A survey on models for panel count data with applications to insurance", *RACSAM: Revista de la Real Academia de Ciencias Exactas, Físicas y Naturales, Serie A, Matemáticas*, Vol. 103 (2), pp. 277-294.

Cameron, A.C. and Trivedi, P.K. (1998), *Regression Analysis of Count Data*, Cambridge University Press, New York, NY.

Dabbert, S. (2011), "*Improving the organic certification system*. D 24 of the CERTCOST project", available at: http://www.certcost.org/Lib/CERTCOST/Deliverable/D24.pdf. (accessed 23 september 2011).

DEFRA (2012), *Organic Statistics 2011*, Department for Environment, Food and Rural Affairs, London, UK.

EEC (1991), "Council Regulation (EEC) No 2092/1991 of 24 June 1991 on organic production of agricultural products and indications referring there to on agricultural products and foodstuffs", *Official Journal of the European Union*, Vol. L198, 24 June, pp. 1-101.

EC (2002), "Council Regulation (EC) No 178/2002 of 28 January 2002 laying down the general principles and requirements of food law, establishing the European Food Safety Authority and laying down procedures in matters of food safety", *Official Journal of the European Union*, Vol. L31, 1 February, pp. 1-40.

EC (2007), "Council Regulation (EC) No 834/2007 of 28 June 2007 on organic production and labelling of organic products and repealing Regulation (EEC) No 2092/91", *Official Journal of the European Union*, Vol. L189, 20 July, pp. 1-122.

EC (2012), "List of Bodies or Public Authorities In Charge of Inspection Provided for In Article 15 of Regulation (EEC) No 2092/91". *Official Journal of the European Union,* Vol. C72/08, 10 March, pp. 29-43.

Feinstein, J.S. (1991), "An econometric analysis of income tax evasion and its detection", *RAND Journal of Economics"*, Vol. 22(1), pp. 14-35.

Gambelli, D., Solfanelli, F., and Zanoli, R. (2012a), "Un sistema di certificazione risk-based per i controlli in agricoltura biologica: un'applicazione tramite Bayesian networks", *Rivista di Economia Agro-alimentare,* Vol. 2, pp. 21-41.

Gambelli D., Solfanelli F., and Zanoli R. (2012b) "Measuring the risk of non-compliance in Italian organic farms with parametric and non-parametric models", New Medit, 4, 35-38.

Gambelli D., Zanoli R., and Solfanelli F. (2012) "A decision network for inspections in organic farms in Italy", Frontiers in Artificial Intelligence and Applications, Vol. 238, pp. 403-408.

Greene, W.H. (1994) "Accounting for Excess of Zeros and sample Selection in Poisson and Negative Binomial Regression Model", working paper, Department of Economics, Stern School of Business (USA), New York.

Greene W.H. (2007), *LIMDEP 9.0 Reference Guide Vol. 2,* Econometric Software Inc., Plainview, NY.

Greene, W. H. (2008), *Econometric Analysis, 6th edn,* Prentice Hall, New Jersey, USA.

Hutter, B.M. and Amodu, T. (2008), "Risk regulation and compliance: food safety in the UK", LSE, London.

Lambert, D. (1992), "Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing", Technometrics, Vol. 34 (1), pp. 1-14.

Lampkin, N., Measures, M., and Padel, S. (2011), *2011/12 Organic Farm Management Handbook*, Organic Research Centre, Newbury, UK.

Moschitz, H. (2011), "The potential of alternative certification systems" D21 of the CERTCOST project",available at 13http://www.certcost.org/Lib/CERTCOST/Deliverable/D21.pdf. (accessed 23 december 2011).

Mullahy, J. (1986), "Specification and Testing of Some Modified Count Data Models", *Journal of econometrics*, Vol. 33, pp. 341-365.

Padel, S. (2001), "Conversion to organic farming: a typical example of the diffusion of an innovation?", *Sociologia Ruralis*, Vol. 41 (1), pp. 40-61.

Padel, S. (2008), "Values of organic producers converting at different times: results of a focus group study in five European countries", *International Journal of Agricultural Resources, Governance and Ecology*, Vol. 7, pp. 63–77.

Padel, S. (2010), "The European Regulatory Framework and its Implementation in Influencing Organic Inspection and Certification Systems in the EU. Deliverable 11 of the CERTCOST project", available at: http://certcost.org/Lib/CERTCOST/Deliverable/D14_D11.pdf. (accessed 23 september 2010).

Rehber, E. (2011), Economics of Organic Farming (Extended and updated), Lambert Academic Publishing, Saarbrücken, Germany.

Rigby, D., Young, T., and Burton, M. (2001), "The development of and prospects for organic farming in the UK", *Food Policy*, Vol. 26, pp. 599-613.

Stolze, M., Hartmann, M., and Moschitz, H. (2012), "Report on total costs of three organic certification systems in six european countries with particular focus on organic supply. Deliverable 21 of the CERTCOST project", available at: http://www.certcost.org/Lib/CERTCOST/Deliverable/D21_B.pdf. (accessed 23 September 2012).

Schmidt, O. and Huber, B. (2007), "Comparison of the EEC Reg.2092/91 and selected national and international organic standards as regards compliance and identification of specific areas where harmonisation, regionalisation or simplification may be implemented in EEC 2092/91' EEC 2092/91 (Organic) Revision. Project report D 3.2. Frick, Forschungsinstitut Biologischer Landbau (FIBL), available at: http://orgprints.org/13101/1/schmid-etal-2007-final-report_organic-revision.pdf (accessed 23 September 2012).

Sandmo, A. (2002), "Efficient Environmental Policy with Imperfect Compliance", *Environmental and Resource Economics*, Vol. 23, pp. 85-103.

Van Asselt, E. D., Sterrenburg, P., Noordam, M.Y., and Van der Fels-Klerx, H. J. (2012), "Overview of available methods for risk based control within the European Union", Trends in Food Science & Technology, **23**, 51-58.

Willer, H. and Kilcher, L. (2010), *The World of Organic Agriculture - Statistics and Emerging Trends 2010*, IFOAM and FiBL, Bonn- DE and Frick-CH.

Winkelmann, R. and Zimmermann, K.F. (1995), "Recent developments in count data modelling: Theory and applications", *Journal of Economic Surveys*, Vol. 9, pp. 1-24.

Winkelmann, R. (1996), "Markov Chain Monte Carlo Analysis of Underreported Count Data With an Application to Worker Absenteeism", *Empirical Economics*, Vol. 21, pp. 575-587.

Zorn, A., Lippert, C., and Dabbert, S. (2012), "Supervising a system of approved private control bodies for certification: The case of organic farming in Germany', Food Control, Vol. 25(2), pp. 525-532.

Zorn, A., Lippert, C., and Dabbert, S. (2013), "An analysis of the risks of non-compliance with the European organic standard: a categorical analysis of farm data from a German control body", Food Control, Vol. 30, pp. 692-699.

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Dr Francesco Solfanelli (researcher), PhD. in Informatics, Managerial and Automatics Engineering (Università Politecnica delle Marche) lectures in farm economics at the Università Politecnica delle Marche. He has participated to various research projects in the field of organic farming, with experience in quantitative modelling.

Dr. Susanne Padel (Research Associate), PhD. in Agricultural Economics (UWA), experience in organic regulation, standards, values and principles, qualitative social science methods; organic sector and market development in UK and Europe, planning and business analysis of organic farms.

Table 1

Organic land area timeseries UK

Products (1000 Ha)	2007	2008	2009	2010	2011	% change 2011/2010
Cereals	52	57	60	57	52	-7.7
Other arable crops	11	11	11	11	9	-14.1
Fresh vegetables (inc potatoes)	17	20	19	18	16	-12.7
Fruit and nuts	2	2	2	2	2	-5.1
Herbaceous & ornamentals	1	6	6	6	6	-1.0
Temporary pastures	125	130	126	125	116	-6.9
Permanent pastures (inc.rough grazing)	452	494	496	479	435	-9.2
Woodland	11	6	7	8	8	2.5
Unutilized land	11	18	12	12	11	-12.1
Total organic land area	682	744	739	718	656	-8.7

Source: DEFRA, 2012.

Table 2

Classification of non-compliance (NC)

Type of NC	Effects of NC
Minor	Does not directly compromise the integrity of the product but needs correction.
Major	May compromise the integrity of the product if not corrected, or may result from not correcting a previous minor non-compliance
Critical	Directly affects the integrity of the product, or may result from not correcting a previous major non-compliance. A critical non-compliance will normally result in the withdrawing of certification from the products or enterprises affected or the whole licence.
Manifest	Integrity in the organic system has been lost. Manifest non-compliance may also result from not correcting a previous critical noncompliance. License could be partly or completely withdrawn. This category can only be noted by the inspector during the visit but is only issued after confirmation by the certification department and not stored in the same database.

Source: Information provided by the Soil Association (2010)

Table 3

Distribution of farms by number of noncompliance (NC) and year

	Minor NC			**Major NC**			**Critical NC**		
	2007	**2008**	**2009**	**2007**	**2008**	**2009**	**2007**	**2008**	**2009**
Total farms	1,747	2,069	2,096	1,747	2,069	2,096	1,747	2,069	2,096
Farms with no NC	1,139 (65.2%)	1,254 (60.6%)	1,321 (63.0%)	1,646 (94.2%)	1,906 (92.1%)	1,905 (90.9%)	1,733 (99.2%)	2,056 (99.4%)	2,051 (97.8%)
Farms with at least 1 NC	608 (34.8%)	815 (39.4%)	775 (37.0%)	101 (5.8%)	163 (7.9%)	191 (9.1%)	14 (0.8%)	13 (0.6%)	45 (2.2%)
of which:									
Farms with 1 NC	311 (51.2%)	428 (52.5%)	449 (57.9%)	73 (72.3%)	126 (77.3%)	154 (80.6%)	12 (85.7%)	12 (92.3%)	40 (88.9%)
Farms with 2 NC	152 (25.0%)	205 (25.2%)	178 (23.0%)	17 (16.8%)	26 (16.0%)	25 (13.1%)	1 (7.1%)	1 (7.7%)	5 (11.1%)
Farms with 3 NC	80 (13.2%)	99 (12.1%)	75 (9.7%)	6 (5.9%)	9 (5.5%)	7 (3.7%)	0 (0.0%)	0 (0.0%)	1 (0.0%)
Farms with 4 NC	31 (5.1%)	48 (5.9%)	32 (4.1%)	2 (2.0%)	1 (0.6%)	3 (1.6%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Farms with 5 NC	16 (2.6%)	18 (2.2%)	18 (2.3%)	2 (2.0%)	0 (0.0%)	0 (0.0%)	1 (7.1%)	0 (0.0%)	0 (0.0%)
Farms with NC≥ 6	18 (3.0%)	17 (2.1%)	23 (3.0%)	1 (1.0%)	1 (0.6%)	2 (1.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

Table 4

Potential risk factors for noncompliance (NC) considered in Model 1 and Model 2

Variable	*Description*	*Mean*
General risk factors		
Arable farm type	= 1 yes; = 0 no	0.247
Horticulture farm type	= 1 yes; = 0 no	0.050
Livestock farm type	= 1 yes; = 0 no	0.465
Mixed farm type	= 1 yes; = 0 no	0.237
Detection of Minor NC (Model 2 only)	= 1 yes; = 0 no	0.372
Detection of Major NC (Model 1 only)	= 1 yes; = 0 no	0.077
Detection of Critical NC (Model 1, 2)	= 1 yes; = 0 no	0.012
Conventional Area	= 1 yes; = 0 no	0.252
Farmer's experience as organic	Nr of years a farmer is certified by SA Min: 0.03 Max:13.76 s.d.: 2.87	6.436
Farm Size	UAA (ha) (Min: 0.01 Max: 2,598.54 s.d.: 233.25)	137.966
On-farm processing	= 1 yes; = 0 no	0.072
Crops and livestock production		
Cereals	= 1 yes; = 0 no	0.393
Dry Pulses	= 1 yes; = 0 no	0.085
Fruit	= 1 yes; = 0 no	0.143
Grasslands	= 1 yes; = 0 no	0.833
Green Fodder	= 1 yes; = 0 no	0.546
Industrial Crops	= 1 yes; = 0 no	0.074
Root Crops	= 1 yes; = 0 no	0.098
Vegetables	= 1 yes; =0 no	0.243
Cattle	= 1 yes; =0 no	0.499
Pigs	= 1 yes; 0 = no	0.082
Sheep and goats	= 1 yes; 0 = no	0.344
Poultry	= 1 yes; 0 = no	0.153

s.d: standard deviation

Table 5

Result coefficients for the minor and major noncompliance NC ZIP models

Risk factors	Minor NC		Major NC	
	Coeff.	Std. error	Coeff.	Std. error
Poisson-count regime				
Cereals	.10832*	.04214	.07099	.10997
Dry pulses	-.08581	.06114	-.14409	.18121
Fruit	-.00800	.05194	-.28164	.18528
Grasslands	-.04226	.05684	.20279	.16441
Green fodder	.25406***	.03992	.30896**	.10433
Industrial crops	.21826***	.05770	.03559	.18147
Root crops	.21260***	.05447	-.21276	.18204
Vegetables	.06193	.04438	-.04261	.13362
Cattle	.11913**	.03954	.05030	.11851
Pigs	.21502***	.05770	.43967**	.16294
Sheep & Goats	.10520 **	.03840	.02077	.11197
Poultry	.11156*	.04753	-.00448	.14541
Constant	-.42734**	.06100	-1.67446***	.18903
Zero-count (logit) regime				
Farm size	-.03830	.02273	-.06013	.03278
Conventional area	-.17604	.10716	-.16131	.15683
On-farm processing	-.16316	.17575	.13830	.26061
Farmer's experience as organic	.03008	.01560	.02805	.02431
Minor non-compliance			-1.52047***	.14221
Major non-compliance	-2.67441***	.54042		
Critical non-compliance	-2.52255	141.482	-10.16502	1003.47094
Arable farm type	.14153	.20412	.24193	.42083
Livestock farm type	-.54894**	.20408	.19207	.42674
Mixed farm type	-.34627	.20992	.25345	.42837
Constant	-.14130	.21558	1.47001**	.45001
Nr Observations	5,912		5,912	
AIC	2.239		.624	
BIC	2.266		.652	
Lr Test Panel vs Pooled	.000		.000	
Vuong test Zip vs Poisson	-87.190		-33.693	

*Levels of significance: * p<.05; ** p<.01; *** p<.001*