Universität Hohenheim

Fakultät Agrarwissenschaften

Institut für Landwirtschaftliche Betriebslehre (410a)

Fachgebiet Produktionstheorie und Ressourcenökonomik im Agrarbereich

Prof. Dr. Stephan Dabbert

Economic analysis of organic certification systems: Determinants of non-compliance and optimum control strategies

Kumulative Dissertation

zur Erlangung des Doktorgrades der Agrarwissenschaften der

Fakultät Agrarwissenschaften der Universität Hohenheim

vorgelegt von

Alexander Zorn

Stuttgart-Hohenheim, 2012

Prüfungskommission

Datum des Promotionskolloquiums	3. Mai 2012
Berichter und Betreuer:	Prof. Dr. Stephan Dabbert
Mitberichter:	Prof. Dr. Tilman Becker
Prüfer (mündlich):	Prof. Dr. Manfred Zeller
Leiter des Kolloquiums:	Prof. Dr. Harald Greth

Vorwort

Diese Dissertation entstand im Rahmen des Forschungsprojektes „*CERTCOST – Economic analysis of certification systems for organic food and farming*“, das von der Europäischen Union innerhalb des 7. Forschungsrahmenprogramms gefördert wurde. Die Projektarbeit ermöglichte mir, mit Wissenschaftlern und Praktikern aus verschiedenen Ländern zusammen zu arbeiten. Dabei konnte ich viele wertvolle fachliche und persönliche Erfahrungen sammeln. Für diese Möglichkeiten und die kontinuierliche Unterstützung bei der Erstellung dieser Arbeit möchte ich Herrn Prof. Dr. Stephan Dabbert herzlich danken. Zum Gelingen der Arbeit hat insbesondere Herr Prof. Dr. Christian Lippert beigetragen, der mir stets als kompetenter Ansprechpartner zur Verfügung stand. Schließlich möchte ich allen Mitarbeitern, mit denen ich am Institut für Landwirtschaftliche Betriebslehre zusammenarbeiten durfte, für die freundliche Arbeitsatmosphäre und die konstruktive Zusammenarbeit danken.

Stuttgart-Hohenheim, im Mai 2012 Alexander Zorn

Contents

List of tables

List of figures

List of abbreviations

BIC	Bayesian information criterion
BLE	Bundesanstalt für Landwirtschaft und Ernährung (*Federal Office for Agriculture and Food*)
BMELV	Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz (*Federal Ministry of Food, Agriculture and Consumer Protection*)
CB	Control body
cf.	Compare (*Latin: confer*)
Coef.	Coefficient
Conf.	Confidence
DC	Consumer damage
DE	Ecological damage
DG Agri	Directorate General for Agriculture and Rural Development
DS	Sectoral damage
e.g.	For example (*Latin: exempli gratia*)
EC	European Communities
EN	European norm
EU	European Union
f.	And the following [page]
FAO	Food and Agriculture Organization of the United Nations
GMO	Genetically modified organism
i.e.	That is (*Latin: id est*)
ISO	International Organization for Standardization
km²	Square kilometre
LR	Likelihood ratio
OECD	Organisation for Economic Co-operation and Development
ÖLG	Öko-Landbaugesetz
p.	Page
R^2	Coefficient of determination
SME	Small and medium-sized enterprises
Std.Err.	Standard error
TOS	The Organic Standard
UAA	Utilized agricultural area
WHO	World Health Organization
WTO	World Trade Organization
%	Percent

Symbols used in the heuristic model are documented separately in Chapter 5.7 "*Annex: List of symbols used*"

Zusammenfassung

Systeme zur Zertifizierung ökologischer Produktion (im Folgenden Öko-Kontrollsysteme genannt) sind die notwendige Voraussetzung für die Existenz eines großräumigen Marktes für ökologische Lebensmittel. Trotz eines etablierten und im Allgemeinen wirksamen Kontrollsystems kommt es regelmäßig zur Aufdeckung von Betrugsfällen, die der Öko-Kontrolle entgangen sind. Die vorliegende kumulative Dissertation besteht aus vier Artikeln, die aktuelle Fragestellungen behandeln, wie Öko-Kontrollsysteme verbessert werden können.

Einleitend wird anhand eines spieltheoretischen Modells die Notwendigkeit für die staatliche Überwachung eines Kontrollsystems, das auf privaten Kontrollstellen basiert, aufgezeigt. Die Kontrollergebnisse möglicherweise beeinflussende Faktoren werden systematisch dargestellt. Auf dieser Basis werden deutsche Daten, die zur Überwachung des Systems in den Jahren 2006 bis 2008 erhoben wurden, statistisch untersucht. Diese Untersuchung zeigt, dass es zwischen Kontrollstellen signifikante Unterschiede hinsichtlich der ausgesprochenen schweren Sanktionen, d.h. wesentlicher Kontrollergebnisse gibt. Die Daten zur Überwachung des Systems können jedoch nicht zur weiteren Analyse der Ursachen dieser Unterschiede beitragen. Dieses Manko resultiert aus der Unzulänglichkeit der erhobenen Daten: für die Erhebung wesentliche Begriffe sind nicht definiert und die Definition von Merkmalen scheint sich im Zeitverlauf zu ändern. Die Analyse zeigt, dass detailliertere und verlässlichere Daten erforderlich sind, um die Bestimmungsgrößen für die Nichteinhaltung von Öko-Standards besser zu verstehen.

Detaillierte Daten der Öko-Kontrolle landwirtschaftlicher Betriebe wurden von zwei Kontrollstellen für die Jahre 2007 bis 2009 zur Verfügung gestellt. Hypothesen zu Faktoren, die die Nichteinhaltung des Öko-Standards beeinflussen können, werden mit Hilfe des Ansatzes der „*Economics of Crime*“ abgeleitet. Die Daten von jeweils einer Kontrollstelle aus Deutschland und der Schweiz werden mittels ökonometrischer Modelle untersucht. Zur Analyse werden zwei unterschiedliche logistische Regressionsmodelle herangezogen. Mit diesen Modellen wird unter Verwendung der Daten zur Betriebs- und Produktionsstruktur auf einzelbetrieblicher Ebene die Sanktionswahrscheinlichkeit geschätzt, die als Proxy-Variable für die Nichteinhaltung des jeweiligen Öko-Standards

genutzt wird. Dieser Ansatz zur Bestimmung von Faktoren, die die Nichteinhaltung beeinflussen, wurde bisher in der wissenschaftlichen Literatur noch nicht verwendet.

Die Daten der deutschen Kontrollstelle beinhalten abgestufte Sanktionen. Daher werden diese mittels eines ordinalen logistischen Regressionsmodells analysiert. Zur Analyse der schweizerischen Kontroll-Daten wird ein logistisches Random-Effects-Panelmodell verwendet. Beide Modelle bestätigen einige der bislang in der Praxis zur Analyse des Risikos der Nichteinhaltung benutzten Kriterien. Die Kontrollergebnisse der Vorjahre, die Komplexität der landwirtschaftlichen Betriebe insgesamt sowie die tierproduktionstechnischen Herausforderungen als auch die Betriebsgröße erhöhen die Wahrscheinlichkeit der Sanktionierung. Ein mit besonderen Frucht- oder Tierarten verknüpftes Risiko, das sich z.B. aus besonderen Ansprüchen eines bestimmten Produktionsverfahrens ableiten ließe, kann über die Modelle hinweg nicht festgestellt werden. Der nicht völlig zufriedenstellende Erklärungsgehalt beider Modellansätze legt nahe, zukünftig Variablen zu berücksichtigen, die bisher nicht erhoben wurden. Insbesondere persönliche Eigenschaften des Betriebsleiters oder Daten zur finanziellen Lage des Betriebs bzw. des Betriebsleiters könnten den Erklärungsgehalt erhöhen.

Das heuristische Modell baut auf den ökonometrischen Modellen auf. Dieses Modell untersucht das Kontrollsystem aus volkswirtschaftlicher Sicht, da es die Kosten der Kontrolle gemeinsam mit den Schäden der Nichteinhaltung eines Öko-Standards berücksichtigt. Die Zusammenhänge zwischen relevanten Bestimmungsgrößen werden mittels Monte-Carlo-Simulationen beleuchtet, um Rückschlüsse zur Optimierung des Kontrollsystems zu ermöglichen. Diese Simulationen zeigen, dass selbst ohne Geldbußen ein Zustand eintreten kann, bei dem ein Großteil der Farmer den Standard einhält.

Die zur Analyse verwendeten Ansätze sind jeweils mit typischen, den Kontrolldaten anhaftenden Schwierigkeiten verbunden. Dazu gehören die Dunkelziffer der unentdeckten Nichteinhaltung, unterschiedliche Aufdeckungswahrscheinlichkeiten (z.B. zwischen unterschiedlichen Produktionsverfahren) sowie ein möglicher positiver Bestätigungsfehler, der aus der Anwendung von risikobasierten Kontrollansätzen resultieren kann. Die dieser Arbeit zugrunde liegende Arbeitshypothese, dass diese möglichen Verzerrungen jeweils zufällig verteilt sind, sollte in zukünftigen Untersuchungen näher erforscht werden.

Solch zukünftige Studien sollten auf der Basis noch differenzierterer Daten durchgeführt werden. Dazu könnten beispielsweise die Daten mehrerer Kontrollstellen in einem Datensatz zusammengeführt werden. Eine breitere Datengrundlage könnte auch die verlässliche Analyse schwerer Nichteinhaltungen ermöglichen, die selten vorkommen. Überdies würde es solch ein Datensatz erlauben, für die Überwachung des Kontrollsystems wesentliche Fragestellungen zu überprüfen. Dazu gehört zum Beispiel die Existenz eines Kontrollstelleneffektes auf die Kontrollergebnisse.

Diese Arbeit präsentiert wichtige Ergebnisse, die für zukünftige Analysen von Öko-Kontrollsystemen herangezogen werden können. Darüber hinaus sind der vorgestellte Ansatz, die angewandten Methoden sowie die Erkenntnisse von generellem Interesse für Zertifizierungssysteme auch außerhalb des Bereichs ökologisch hergestellter Lebensmittel.

Summary

Organic certification systems are prerequisite for the existence of a large-scale organic food market. Despite a well-established and generally effective control system, fraud regarding organic food that passed organic controls is detected regularly. This cumulative thesis consisting of four articles addresses current questions regarding the improvement of organic certification systems.

The need for governmental supervision of an organic certification system run by private control bodies is demonstrated by a game theoretic model. A framework prepares the statistical analysis by conceptually linking factors that can influence organic control results. The case study on German supervision data from the years 2006 to 2008 reveals significant differences between private control bodies regarding the number of severe sanctions imposed, i.e. fundamental control results. These data that were collected for supervision of the control system, however, are not sufficient to explain these differences. This is due to shortcomings in the data collected. Key terms of the data are not defined and the variable definitions seem to change over time. This study concludes that there is more detailed and reliable data from organic control bodies needed to understand the determinants of non-compliance with an organic standard.

Detailed data on organic farm controls from the years 2007 to 2009 were supplied by two control bodies. Theoretical considerations founded on the "*Economics of Crime*" approach yield hypotheses on factors affecting non-compliance with an organic standard. The data provided by a German and a Swiss control body are analysed by two different logistic regression models. The probability of receiving a sanction (which is used as proxy for non-compliance) is estimated on farm level by using data on farm and farm production. Such an approach to assess the determinants of non-compliance has not been used previously in the literature.

Given the gradual sanction system, an ordinal logistic regression model is appropriate for the analysis of the German data. Swiss data are analysed by a random effects logistic regression model. Both models confirm some of the factors contributing to the risk of non-compliance that are applied in qualitative risk assessment so far. Control results from previous years, the overall farm complexity and the farm livestock production complexity, as well as farm size are factors that increase the probability of receiving a sanction. Risks connected to specific crops or livestock types that could come along, e.g., with particular requirements of the production method cannot be confirmed across the models. The explanatory value of both models is likely to be improved by the integration of further variables, such as data on farmers' personal and financial characteristics.

The heuristic model builds on the results of the econometric models. This model adopts a societal view on the control system by considering the costs of controls and the damages resulting from non-compliance with an organic standard. Monte-Carlo simulations illustrate the relationship between important parameters for optimising control strategies. These simulations show that even without fines a situation can occur where most operators comply.

The different approaches to analyse control data encounter difficulties inherent to the control data. In this context, the dark figure consisting of undetected non-compliances, inhomogeneous detection probabilities linked to particular production methods, and a potential positive confirmation bias connected to the risk based control approach are especially relevant. The working hypothesis that these potential biases are distributed randomly deserves closer attention in subsequent studies.

Such future analysis should be based on even more detailed data, e.g., pooling original data from different control bodies in a control system. Such a data base would allow focusing on severe non-compliances which occur only rarely. Furthermore, pooled data could be used to investigate issues that are fundamental for the supervision of a control system such as a control body effect on the detection of non-compliance.

This thesis presents important results that can be consulted for further analysis of organic control systems. Beyond, the approach, the methods used, and the results obtained are of general relevance for food certification systems beyond the organic sector.

1 Introduction

Certification systems today are widespread in the agricultural sector. Thus, information on products and production processes is provided to business partners and consumers: certification systems can make invisible attributes of food visible.

The European organic farming sector is continuously growing (European Commission - DG Agri, 2010). The growth of the organic market depends on a credible organic control system which is a basic requirement for a separate organic market (Dabbert et al., 2004). The managerial and financial charges ("*bureaucracy*") of the organic control system are considerable. For some farmers, these burdens are the cause not to convert to organic farming or to reconvert (Rigby et al., 2001; Flaten et al., 2010).

The "*Rat für Nachhaltige Entwicklung*" (German Council for Sustainable Development) recently ennobled organic farming standards as "*Gold-Standard*" in recognition of the relevance of organic farming for a sustainable agriculture (Rat für Nachhaltige Entwicklung, 2011). The German government pursues the objective of a 20% area share of organic farming in its national sustainability strategy (Die Bundesregierung, 2008). The achievement of this objective depends on a similar growth of the organic market, which requires an effective organic control system so that consumers can trust in organic labels.

The work underlying the four articles presented in this thesis was accomplished in the research project CERTCOST "*Economic analysis of certification systems for organic food and farming*"[1] ending in November 2011 (Dabbert et al., 2008). In this project, research institutions and small and medium-sized enterprises (SME) from seven countries combined their efforts to analyse organic controls[2] from different perspectives. The background of such a research project with participation of SME from the organic control sector offered the opportunity to get and use data from different institutions, such as the "*Bundesanstalt für Landwirtschaft und Ernährung*" (BLE – Federal Office for Agriculture and Food) and different private control bodies. Among these control bodies' data, those of a German and a Swiss control body were used for analysis in this thesis.

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1 For further information, please refer to the project homepage: www.certcost.org.

2 In the following text, the terms "*control*" and "*inspection*" are used synonymously. The parallel use of these terms results from a change in terminology of the European organic regulation: while regulation 2092/91 used the term "*inspection*", the current regulation 834/2007 uses "*control*".

The relevant legal framework of organic food and farming in Germany and Switzerland is similar[3], thus, the legal requirements are only described for the German control system based on the European regulation on organic production and labelling of organic products. (Reg. (EC) 834/2007).

The following subchapter introduces the general framework of food and farm certification. Chapter 1.2 illustrates the economic reasoning for organic certification. The concept of risk based controls is introduced and discussed in Chapter 1.3 with regard to its implementation in organic control systems. Then, different methods by which non-compliance with an organic standard can be analysed are presented in chapter 1.4. Finally, an overview on the objectives and the organisation of this thesis is given.

1.1 Food standards and certification

Today's agricultural and food production is increasingly governed by standards (Hatanaka et al., 2005). A standard specifies rules, e.g., how a product shall look like or how the production process shall be conducted. These rules intend to achieve defined product and process qualities to meet the specific demand of processors and consumers. Such standards are controlled for adherence, typically by an independent *third* party (next to seller as *first* and buyer as *second* party). In case of non-compliance with a standard, an enforcement system consisting of subsequent measures and actions is present. The assurance that a production process or a product is in conformity with a certain standard is then given in written form by a certificate (Codex Alimentarius Commission, 1995). The consumers can identify certified products by a label[4].

Codifying rules on food quality and labelling date back to the ancient world[5]. Today, the Codex Alimentarius Commission is the international reference point for food standard issues. The Codex Alimentarius Commission was established in the 1960s by the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) (FAO and WHO, 2006). Food standards evolved and diversified

[3] According to an equivalency agreement between Switzerland and the European Union, their organic regulations correspond mutually (EC, 2002).

[4] Detailed information on economic aspects of food labelling, which is not dealt with in this thesis, is provided by Golan et al. (2001); for a general introduction on organic labelling and consumer preferences, see Janssen and Hamm (2012), respectively.

[5] The oldest documents on "*food standards*" date back to the pre-Christian time, to the Assyrian and Egypt people (FAO and WHO, 2006).

over the years along with societal demands as well as technological and scientific developments (Smith, 2009).

Examples for the increasing importance of food standards and corresponding certification and labelling are manifold and cover a large variety of areas, such as environmental characteristics, animal welfare, indications of origin, and organic farming standards. At present, environmental, social, and ethical issues are becoming increasingly relevant for consumers (Wissenschaftliche Beiräte für Verbraucher- und Ernährungspolitik sowie Agrarpolitik, 2011). Certification and according labelling is *the* instrument to provide consumers relevant information on the production process of food.

1.1.1 Types of food standards

The multitude of food standards and certification can be structured according to different dimensions. A basic differentiation results from the kind of attributes covered by a standard. A product standard, specifies the attributes of a product (e.g., a marketing standard defining the size, shape or nutritional content) whereas a process standard specifies the attributes of the production process (e.g., an organic standard prohibiting the use of synthetic fertilisers and explicitly stating how to raise livestock). This distinction is of specific relevance for the organic process quality which is not visible to consumers. They have to trust in organic labels to distinguish the organic quality.

Besides, the literature discriminates between public and private standards although the categorisation of these concepts is not perfectly clear[6]. In the context of organic food standards[7] and in this thesis, the distinction is based on the attribute of the institution setting and governing a standard. Public standards result from public, i.e., governmental activities such as the European organic regulation. Private standards are issued by non-governmental organisations such as Bioland in Germany, Bio Suisse in Switzerland or Soil Association in the United Kingdom. The majority of standards are published by private organisations (Brunsson and Jacobsson, 2000). This also applies for the area of organic standards. However, the implementation of state regulations complementing

[6] The World Trade Organisation (WTO) points to the beneficiary of a standard to distinguish private from public standards (WTO, 2005). Yet, in the case of organic standards this criterion is unhelpful as private firms (fair competition), consumers (reliable labelling) and the society (positive environmental externalities) can altogether benefit from organic farming standards and corresponding controls.

[7] In the following text, the term "*organic standard*" is used for organic food standard.

existing private standards is important as the state holds hierarchical power, i.e., the ability to sentence producers not adhering to a standard (Brunsson and Jacobsson, 2000).

Anybody labelling agricultural or food products "*organic*" has to comply with the European organic regulation. Therefore, the European organic regulation can be classified as a mandatory organic standard[8]. Operators must comply with this regulation to enter the organic market, even, if the decision to do so is voluntary. Private organic standards in contrast are considered as voluntary; operators may choose to adhere to these requirements for personal or marketing reasons. If private standards exist in parallel to a mandatory standard, private standards basically imply more strict rules.

1.1.2 Organic food standards

Organic standards are process standards as they specify the process how organic food shall be produced. In Europe exists a basic public organic standard which is considered as mandatory. Beyond, many different private standards exist.

At present, in the European Union, organic food and farming is regulated by a Council Regulation whose scope dates back to the year 1991 (EC, 1991)[9]. This regulation defines the basic prerequisites for the production and labelling of organic agricultural and food products. The fundamentals of organic farming, however, are much older and date back to the 1920s (Vogt, 2001). Then, the trade relationships between organic farmers and their customers were closer and more direct than today; the organic market was very small. Therefore, there was no essential need to define and control explicit production rules for organic food (Schmid, 2007). The rules of the different organic movements became more detailed and increased in volume in the course of time. Hence, formal guidelines (that is to say standards[10]) and corresponding control systems emerged (Vogt, 2001) to protect consumers from fraud with mislabelled organic products and to ensure fair competition between producers (Schmid, 2007).

8 This classification of mandatory organic standards deviates from the general classification used by the World Trade Organisation (WTO) or the Organisation for Economic Co-operation and Development (OECD) (Smith, 2009).

9 Regulation (EC) No 2092/91 was revised some years ago. From January 1st 2009, the revised regulation (EC) No 834/2007 applied as from 1 January 2009 (EC, 2007). The articles in this thesis cover the scope of both regulations.

10 The term standard is used generally and covers also organic regulations of states or federations.

1.2 Economic concepts of organic standards and certification[11]

The need for an organic standard and according certification in an anonymous market economy results from the specific characteristics of organic food that result from the production process. Three basic categories of goods are differentiated according to their characteristics: search, experience and credence goods (Nelson, 1970; Darby and Karni, 1973). Search characteristics can be easily identified prior to purchase, e.g., the colour of a tomato. Experience characteristics can only be ascertained after the purchase by using or consuming a good, e.g., the taste of the tomato. Finally, credence characteristics cannot easily (at low cost) be checked, neither before nor after the purchase, e.g., the organic quality of the tomato. Organic food exhibits credence characteristics. The information costs for consumers to assess the quality increase from search to credence attributes.

While the consumer has to spend time and also money to gather quality information, the seller normally is better informed on the quality attributes of items for sale. This information asymmetry is most pronounced in case of credence goods. The presence of information asymmetries can result in market failure, namely adverse selection (Akerlof, 1970; Fritsch et al., 2003) and favours opportunistic behaviour, e.g., fraud regarding the true organic quality (McCluskey, 2000).

From the viewpoint of institutional economics, an organic standard can be considered as an institution, i.e., as a system of norms targeting to particular goals and comprising instruments of enforcement. Institutions intend to govern individual behaviour. The definition of rules, their control and enforcement shall guarantee certain aspects of quality. Transactions are simplified and market transaction costs, i.e., the costs of exchanging goods on the market, can be decreased (Furubotn and Richter, 2005).

Thus, organic control systems reduce consumers' information costs and overall market transaction costs and they reduce the information asymmetry. Hereby, organic control systems facilitate market transactions, increase market efficiency and ensure the functioning of organic markets (Golan et al., 2001).

[11] This section draws on the report "*Economic concepts of organic certification*" by (Zorn et al., 2009).

1.3 Risk based control approaches[12]

Risk characterises situations where the probability for the occurrence of an event is known. A situation in which no information on the probability of occurrence is available is referred to as uncertainty (Knight, 1971; Dabbert and Braun, 2006). Risk based control approaches intend to consider the relevant available information when determining control strategies and plans. The basic concept of risk based control approaches is to focus control resources on operators and control areas supposed to show higher risk of non-compliance.

The European organic regulation requires a risk based control approach: "*In the context of this Regulation the nature and frequency of the controls shall be determined on the basis of an assessment of the risk of occurrence of irregularities and infringements as regards compliance with the requirements laid down in this Regulation*" (Art. 27(3) of Reg. (EC) 834/2007 (EC, 2007)).

The nature of organic controls is mainly characterised by the announcement of a control (announced versus unannounced controls), the coverage (e.g., a complete control of an operation versus partial controls), the control area (e.g., field visit versus control of movements of goods versus analysis sample), and the location (on-site versus remote control, i.e., from the control body's office). These attributes of organic controls and their combinations offer specific control approaches to a multitude of possible risk situations.

The control frequency shall depend on the risk of non-compliance. The regulation requires one annual control of every organic operator. More frequent controls therefore mean more controls in addition to the regular annual control.

Crucial questions of any risk based control approach are the criteria and the method used when evaluating the risk. Regarding the criteria, the European implementation regulation requires "*taking into account at least the results of previous controls, the quantity of products concerned and the risk for exchange of products*" (Art. 65(4) of Reg. (EC) No 889/2008 (EC, 2008)). The specified criterion "*quantity of products concerned*" directs the attention to an issue not considered in the basic regulation: the potential damage resulting from non-compliance, e.g., the damage of deceived consumers or the loss of reputation for the organic sector. Such damages are likely to increase with the affected

[12] The term "*risk based inspection approach*" is similarly used.

quantity. The damage furthermore depends on the severity of non-compliance. Therefore, further distinction regarding the severity of non-compliance is also relevant. The severity of non-compliance is reflected in the subsequent sanction.

Methods on how to determine the risk of non-compliance, either qualitatively, e.g., by a classification in risk classes or quantitatively, e.g., by non-compliance probabilities, are left up to the control authority or control body.

Substantial literature on the risk based control approach and its implementation exists in the area of food safety (e.g., Food and Agriculture Organization of the United Nations, 2008; Hoffmann, 2010; König et al., 2010). Corresponding literature on the certification of process quality is relatively sparse and rarely exceeds the recommendation to implement such systems (e.g., Schulze et al., 2006; Albersmeier et al., 2009). A German handbook for organic control bodies suggests criteria to evaluate the risk of an operation and criteria to identify organic products with increased risk (Fischer and Neuendorff, 2011). These guidelines suggest evaluating risk categorically. In the end, an operation is ranked in one of four risk classes, each with a different probability of additional spot checks. A recent working document of the European Commission (European Commission - DG Agri, 2011) recommends amongst others to consider national or regional characteristics of the organic market.

Risk based control approaches are considered a promising instrument to enhance certification systems (Jahn et al., 2005). By implementing risk based control approaches, it is expected to "*improve the performance*" of control bodies and authorities (Commission of the European Communities, 2004). As a result it is expected that controls will be more "*efficient and effective*" (Albersmeier et al., 2009; Rundgren, 2010). In short, one could have the impression that the risk based control approach is considered as a "*panacea*" for certification systems. However, it seems that the thorough application and comprehensive use of this instrument is not yet achieved: an organic control expert (Rundgren, 2010) recently stated that "*there is little progress so far*" on risk assessment. Currently, control bodies apply a multitude of individual approaches to assess risk. These approaches are mainly qualitative risk assessments.

So far, purely quantitative empirical analyses of risk in quality control systems are not documented in the literature. This thesis tries to fill important parts of the academic voids regarding risk based approaches. This is performed by means of an analysis of determinants of non-compliance and by heuristically considering control strategies.

1.4 Analysing non-compliance with organic farming standards

The question, if a farmer complies with an organic farming standard seems at first sight simple to answer with "*yes*" or "*no*". However, there exists a multitude of areas where non-compliance occurs, differently affecting organic integrity. Furthermore, different levels of sanctions are applied – reflecting an evaluation of the severity of non-compliance. The classification of both, non-compliance and resulting sanctions, differs considerably between countries (Gambelli et al., 2012). Depending on the specific characteristics of available control data, the adequate econometric model should be selected. This section illustrates important characteristics of organic control data and briefly presents potential modelling approaches.

1.4.1 Organic control data

Control bodies perform at least one annual control of each operation. The characteristics of the control, the farms, farms' production, non-compliances, and resulting sanctions are recorded. These voluminous records are usually stored in structured data base systems. The data are mainly collected for control and certification reasons and to fulfil the regulatory requirements including data provision for governmental supervision and statistical reasons (Zorn et al., 2012). It is not possible to perform econometric analysis without prior processing of organic control data (Moschitz et al., 2009; Gambelli et al., 2012)[13]. Maybe, this technical obstacle partly explains why control bodies mainly rely on qualitative risk assessment.

The data recorded by control bodies report the detected and documented non-compliances. Indeed, there exist non-compliances which were not detected; this dark figure is unknown. Regularly, fraud cases are disclosed by institutions outside the organic control system, e.g., by general food and feed controls (e.g., the case of Robert Franzsander in Germany in 2009 (Thuneke, 2009)) or by tax audits (e.g., the recent case of faked organic certificates in Italy made public in 2011 (BioHandel-online.de, 2011)).

[13] Further details on the data collection processes of control bodies and the availability of data are documented in Moschitz et al. (2009); the efforts required to prepare the econometric analysis are described in Gambelli et al. (2012).

The methods usually used to shed light on dark figures (interviews of offenders, participant observation) are not appropriate in the area of business crime (Bundesministerium des Inneren and Bundesministerium der Justiz, 2006) among which severe non-compliances with organic standards can be categorised.

According to the official German statistics, a very low share, below 0.5% of organic operators, committed severe non-compliance during the years 2009 and 2010 (Bundesrepublik Deutschland, 2010; Bundesrepublik Deutschland, 2011)[14]. The preponderance of compliant operators limits the power of modelling severe non-compliance when a fixed sample is given, as it was the case in the econometric analyses of this thesis, or requires larger samples. Minor non-compliances usually are detected more frequently (Gambelli et al., 2012).

The data on non-compliance generally is not categorised according to severity by control bodies. In a risk based control model, however, the severity of non-compliance is important. As a proxy for the severity of non-compliance, the consequential sanction can be used.

1.4.2 Econometric methods for the analysis of organic control data

For the analysis of categorical variables, different approaches exist. Depending on the information content of the control data, different econometric models are available. A logistic regression model can explain binary outcomes. Such a model is appropriate to explain the sanction probability globally disregarding the severity of a sanction. It can also be applied to explain specific, e.g., only severe sanctions (Urban, 1993; Long and Freese, 2006).

The ordinal logistic regression model additionally considers the severity of a sanction. If the sanction categories can be ordered, such a model can be applied. It uses the information provided by the sanction data more comprehensively than a binary logistic model. The ordinal logistic regression model is based on the assumption of parallel regression. In other words, the estimated probability curves for different sanction

[14] The share of severely non-compliant operators is provided for the years 2009 (0,38%) and 2010 (0,39%) only, since these shares seem reliable as they correspond to other countries' data. In previous years, the shares partly were considerably higher. This can be explained due to missing definitions of central terms, see Zorn et al. (2012).

categories are just “*moved*” (Urban, 1993; Long and Freese, 2006). See chapter 3.4 for further details on the ordinal logistic regression model, which is used for the analysis of German control data.

Panel modelling is also an option, as control data typically consists of repeated (yearly) measurements of the same variables. The organic control data exhibits only little variation (especially regarding the farm structure data) (Gambelli et al., 2012). Fixed effects models are therefore not suited (as time-constant variables are removed prior to estimation). Random effects models assume that the unobserved effects are uncorrelated with the independent variables (Wooldridge, 2006). See chapter 4.3.2 for further details on random effects models, which are used for the analysis of Swiss control data.

These methods, shortly presented, were applied in the econometric analyses in this thesis. Relevant criterion for applying a particular method is the character of the dependent variable, i.e., the sanction imposed. German sanction data feature definite ordinal characteristics, whereas the Swiss sanction data covers 17 different sanctions which cannot be ordered unambiguously.

Furthermore, the characteristics of organic control data principally also allow the application of count data analysis relying on specific probability distributions (Winkelman, 2010). However, the rare occurrence of operators with more than on sanction (i.e., acutal counts) in the available data limits the use of count data models.

1.5 Objectives of this thesis

The preceding text illustrates the setting of organic certification systems from an economic viewpoint. This area offers different research opportunities. Covering societal questions and specific questions on the implementation of an organic control system, for this thesis, the following objectives were selected constituting an expedient overall work:

(1) Demonstrate the need for supervision of certification systems that rely on controls performed by private control bodies.

(2) Develop a theoretical framework for the analysis of certification systems.

(3) Assess the suitability of the data collected for the supervision of organic control systems.

(4) Identify the determinants of non-compliance of organic farmers regarding the adherence to an organic standard.

(5) Synthesise the results of the econometric models in a heuristic model that covers the determinants of non-compliance by considering the societal costs of standard's control and enforcement and the damages resulting from non-compliance.

(6) Demonstrate the effects of important parameters in the model to optimise enforcement measures (control efforts and sanctions).

1.6 Organisation of the thesis

The thesis is based on four articles constituting a cumulative dissertation[15]. One of these articles has been accepted by a peer reviewed journal. Three articles currently are subject to review processes of peer-reviewed journals. The articles are dealing with different present questions regarding certification systems that are of relevance for both, the governance and supervision of a certification system, as well as for its implementation.

The article "*Supervising a system of approved private control bodies for certification: the case of organic farming in Germany*" applies a game theoretic model to show the need for supervision of private control bodies. A framework is developed to analyse the supervision of a control system identifying relevant determinants that influence control results. This framework is of high relevance for the subsequent analysis. Based on German data collected for supervision of the control system, statistical tests are used to assess the suitability of these data for supervision purposes. This work illustrates the need for supervision of private control bodies and the need for an analysis of more detailed control data on operator level.

This need for a quantitative analysis of detailed data is approached by the following two articles. These articles analyse factors contributing to non-compliance based on individual operator data provided by organic control bodies. The analysis of risks for non-compliance is of relevance for both, the supervision of the system and the control planning of control bodies (cf. chapter 1.3). Currently, mainly qualitative risk assessments are applied. This approach can be further developed by complementing the qualitative

[15] The following four chapters each represent one article. These articles are merged in this thesis without perfect harmonisation regarding spelling (mostly British English, but in chapter 5, American English) and the reference systems (the journals' to which the articles have been submitted reference systems is maintained).

assessment with elaborate quantitative analyses. Based on the "*Economics of Crime*" approach (Becker, 1968), hypotheses on factors affecting the probability of non-compliance are derived. These hypotheses are then tested by the help of logistic regression models on operator data to explain sanctions used as proxy for non-compliance.

The article "*An analysis of the risks of non-compliance with the European organic standard: a categorical analysis of farm data from a German control body*" comprises cross-sectional analyses based on ordinal logistic regression models. The data were provided by a German control body and result from organic farm controls against the European organic regulation. The article "*Econometric analysis of non-compliance with organic farming standards in Switzerland*" is based on Swiss control data resulting from a private certification system. Random effects logistic regression accompanied by cross-sectional logistic regression models including time-lagged effects are used for the analysis of Swiss data.

The determinants of non-compliance empirically identified were considered in a broader conceptual approach in the fourth article "*A heuristic model for optimizing the enforcement of organic farming standards*". Based on the decision calculus of an opportunistic farmer, a model is developed considering the cost of inspection, potential fines for non-compliant operators and social damages resulting from non-compliance. The application of this model in different settings of relevant factors illustrates their interplay. This model and the simulations build on the results of the preceding articles and examine the control system and inherent risks from a societal view that is of relevance for supervision and control strategies.

1.7 References

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Zorn, A., C. Lippert and S. Dabbert (2012). "Supervising a System of Approved Private Control Bodies for Certification: The Case of Organic Farming in Germany." Food Control **25**(2): 525-532.

2 Supervising a system of approved private control bodies for certification: the case of organic farming in Germany[1]

Authors: Alexander Zorn, Christian Lippert, Stephan Dabbert

Abstract: Organic food certification by private control bodies (CBs) requires supervision to prevent adverse selection. We investigate whether the official data used for supervision are suitable to assess the control system. To demonstrate the need for supervision, a heuristic game theoretic model analysing different levels of control qualities is presented. Relevant determinants that might explain differences among CBs are discussed. Data analysis is based on data collected from annual supervision reports on the German organic control system from 2006 to 2008. Statistical analysis reveals significant differences among CBs. The data available in the supervision reports are not sufficient to explain the differences identified. Consequences for future data collection on and supervision of European organic control systems are discussed.

Keywords: Organic food, third-party certification, supervision, adverse selection, Germany

Acknowledgements: We are grateful to the anonymous referees for their valuable comments on the manuscript. This publication was generated 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. The publication reflects the views of the authors 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.

[1] This chapter consists of the correspondent article which was accepted by the journal *Food Control* (http://www.journals.elsevier.com/food-control/) on 12 November 2011 and is scheduled to be published in June 2012, doi:10.1016/j.foodcont.2011.11.013. Any reference to this chapter should be cited as: *Zorn, A., C. Lippert and S. Dabbert (2012). Supervising a System of Approved Private Control Bodies for Certification: The Case of Organic Farming in Germany. Food Control* ***25****(2): 525-532.*

2.1 Introduction

An organic certification system is needed for the existence of a functioning organic market (Albersmeier, Schulze, Jahn, & Spiller, 2009; Deaton, 2004; Jahn, Schramm, & Spiller, 2005; McCluskey, 2000; Tanner, 2000). Worldwide, the organic certification sector is dominated by three government-led systems: the European, the U.S., and the Japanese systems, with the European system being the oldest. The European organic certification system allows for different institutional settings and organisational details in different member states of the EU. Particularly interesting are configurations that involve a system of private control bodies (CBs), as in Germany, our case study country.

German organic operators are allowed to choose between different CBs and to change to a different CB if they wish. The free choice of a CB is intended to enhance competition among the different CBs. For a given quality of monitoring and certification, competition at best may lead to lower certification costs for organic operators, thus contributing to lower consumer prices for organic food as well.

However, stiff competition between private CBs might jeopardise the functioning of the organic control system (Anders, Monteiro, & Rouviere, 2007; De & Nabar, 1991; Jahn et al., 2005). According to a survey of 34 CBs in different parts of the world, 9% of the respondents thought “that the competition drove down the tariffs to an unsustainably low level and that it made business survival difficult. Eighteen per cent said that the competition puts a downward pressure on the scrutiny of the controls” (Rundgren, 2009). In the same vein, some organic operators seem to be worried about control quality: a representative of the German *Bioland* association noted that the association receives more phone calls from farmers saying that their supervisor was not strict enough than vice versa (Busse, 2009).

Competition can only work if the quality of services like monitoring and certifying is adequately rewarded. This is usually the case for services with mainly private benefits. With organic certification, however, important benefits are external (i.e., they do not accrue to the firm paying for the service). Therefore, for competing CBs, there might be an incentive to reduce the thoroughness of monitoring to offer certification at a lower fee (Jahn et al., 2005). This problem may be relevant for other realms of food quality certification.

Such a situation would pose a serious problem to the organic market. Consumers assume that organic certification guarantees the organic integrity of the product, regardless of which CB has issued the certificate. Consequently, the European system for organic certification foresees the supervision of private CBs by member state government authorities (European Council, 1991, Art. 9(4)). In turn, these government authorities report to the European Commission.

Our central research question asks whether these official data are suitable to assess the control system. Do the supervision data suggest that there are no differences among CBs? This research question has not been previously analysed in the literature.

We first describe the European organic certification system, including its supervision process, with special reference to the German situation. Next, a heuristic game theoretic model is used to explain the social dilemma we see at the core of the supervision task. We then describe the framework for analysing the supervision of organic certification and relate this framework to previous literature on the topic. Subsequently, we present our data, discuss the results, and conclude.

2.2 The European organic certification system, supervision, and possible determinants of differences among control bodies

The legal basis of the European organic certification system has recently changed. Since January 1, 2009, Reg. (EC) No 834/2007 and the corresponding implementation rule Reg. (EC) No 889/2008 have been in force. However, because our data are from 2006 to 2008, we concentrate on the legal system that was valid during the time that our data were generated. In many aspects, the two legal systems are quite similar.

Under regulation (EC) No 2092/91 (valid until December 2008), the European Union required member states to establish a control system to assure organic quality. Organic operators were controlled for compliance with this organic standard. Member states could opt for one of three different control systems: A, B or C (European Union, 2009).

In System *A*, private CBs perform a third-party certification. These CBs must be approved by the government (i.e., by the “competent authority”). System *B* is a public control system in which the public authority performs the certification and no separate approval is necessary. Finally, System *C* is a mixture of Systems *A* and *B*. We are concerned in this paper with System *A*, which is dominant in the EU; 17 out of 27 member states implemented this system. Germany is the country with the largest number of private CBs among countries adhering to System A.

The approval and subsequent supervision of private CBs include three tasks:

- CBs must be accredited according to European Standard EN 45011 (respectively, ISO Guide 65),
- They must be approved by a designated governmental authority, and
- They must be continuously supervised by the competent authority of a member state.

The authorities of member states are charged with ensuring objective and independent controls and verifying the effectiveness of controls (European Council, 1991, Art. 9(6)). In Germany, this responsibility lies with the Länder (i.e., federal states). The member states report information on the control system and its supervision on an annual basis to the European Commission. These reports are called supervision reports. In Germany, this task is performed by the Bundesanstalt für Landwirtschaft und Ernährung (BLE), which provided the data for this paper.

The BLE is in charge of collecting data from the CBs in the format required by the European Commission. The competent authorities in the Länder also collect data for their own purposes. These latter authorities have additional means of supervising the CBs. For example, they can accompany control visits, and they have the right to see all of a CB’s information on a specific operator. In severe cases of non-compliance, the competent authorities do the sanctioning themselves or forward all necessary information to the appropriate legal system.

This process implies a division of labour between the CBs and the competent authorities, but the details vary among the Länder. To reduce the differences in implementation across the Länder, a working party was established to discuss implementation questions and to provide guidance for the competent authorities. This working party includes all competent authorities in Germany and the BLE. Its decisions are not legally binding, but they are generally adopted by the competent authorities.

The competent authorities thus have a double role: they supervise the CBs, and they perform practical implementation tasks, especially with respect to sanctioning. Because the European Commission can be regarded as the final “owner” of the organic certification system, it makes sense to have a secondary supervision level.

The entire organic control system is ultimately supervised by the European Commission (European Council, 1991, Art. 15) based on the supervision reports provided by the member states. To guarantee an “equally strict control system” (European Commission - DG Agri, 2010), the analysis of national control data is seen as an essential instrument for monitoring the implementation of the European organic regulation in the 27 member states. This article is concerned with this level of supervision.

The European Action Plan for Organic Food and Farming (Commission of the European Communities, 2004) has remarked on variations in the quality of supervision, and the Court of Auditors has pointed to problems with the organic control system and its supervision in a special report (Court of Auditors, 2005). The European Commission seems to be aware that the system continues to struggle with variations in implementation, the “different definitions of the parameters and the different data acquisition” methods (EC, n.d.-c) of the member states (see also EC, n.d.-a; EC, n.d.-b).

Controls in the organic system take different forms. The *annual control visit* of each operator is mandatory (i.e., all operators must be visited by an inspector every year). An additional 10% of operators in Germany (20% in Bavaria) were visited twice during the time that our data were generated (Bundesrepublik Deutschland, 2010). These control visits can take place either *announced* or *unannounced*. The control body can also take samples for testing (for example, for pesticide residues). However, for Germany, the competent authorities have prescribed no minimum number of samples.

“Irregularities” and “infringements” may be found among the results of the controls and the certification process. These terms are given but not explicitly defined in the respective regulations either before or after the recent reform. Following regulation (EC) No 2092/91, an irregularity shall result in a sanction according to Article 9(9a) (i.e., removal of the organic label from the product/lot), and an infringement shall result in a sanction according to Article 9(9b) (i.e., prohibition of organic marketing for the operator). According to the legal notion of commensurability, it is obvious that irregularities and infringements refer to more severe cases of non-compliance and thus indicate a subset of overall non-compliance. Furthermore, it can be inferred that an infringement is more severe than an irregularity.

It is important to note that the lack of a common definition is likely to affect the reliability of the data. Data collection that does not follow a unified process might be one possible reason for the differences among CBs. This shortcoming was mentioned in the first “Report on Supervision” (EC, n.d.-a.) on the year 2005 by the European Commission, and it persists to the present.

2.3 Why supervision of control bodies is needed: a game theoretic model

Honest operators acquainted with and committed to organic farming do not need scrupulous control of *their own* farms; they know that they produce organic quality and comply with all relevant rules for the organic production process. For such operators, the function of an organic certification system is to ensure that all other (perhaps opportunistic) organic operators comply with the relevant standard. Non-compliance by other organic operators might damage the collective reputation of organic products and be detrimental to the marketing of honest operators. Ensuring this collective reputation could become difficult in a situation in which several CBs offer certification for different fees at different degrees of thoroughness.

The following heuristic example illustrates this problem. Imagine an organic market that consists of a given number of good, honest, and skilled operators (i.e., “committed operators”) (j) and three opportunistic operators (i.e., “non-committed operators”) (i = 1, 2, 3). Every operator can choose between two CBs with a different attitude. For simplicity, we distinguish a “rigorous” CB and an “easy-going” one. Both bodies ask for fees, which are private costs borne by the operators. They provide some private benefits, such as extension services. Strictly speaking, CBs are not allowed to explicitly perform extension services. In practice, however, a skilfully performed control visit can help an operator to identify possible improvements in his operation that would not have been detected otherwise. This could be termed “implicit extension” and entails a private benefit.

In the case of non-committed operators, the overall private benefits from the rigorous CB are lower because of higher compliance costs; this body forces the operator to fulfil all rules. Only the rigorous CB contributes to safeguarding the external benefit of the collective reputation. For every non-committed operator certified by the rigorous body, the overall net benefit of every operator increases by a certain amount as fewer scandals will occur. This example results in the following payoff equation for a non-committed operator *i* when certified by a rigorous CB:

$$Payoff_i = -c_P + b_{Pi} + s_i b_E \text{ ,} \tag{2.1}$$

The corresponding equation for a committed operator *j* is:

$$Payoff_j = -c_P + b_{Pj} + s_i b_E, \tag{2.2}$$

with

c_P	Private cost (i.e., certification fee)
b_E	Every supplier's external benefit because of good monitoring and avoided losses to the collective reputation due to strictly monitored non-committed suppliers
b_{Pi}	Private benefit of a non-committed operator (i.e., the value of extension services minus additional compliance cost)
b_{Pj}	Private benefit of a committed operator (i.e., the value of extension services and/or the so-called "good feelings" from supporting a good CB)
s_i	Number of non-committed operators selecting a rigorous CB ($0 \leq s_i \leq 3$)

A possible setting of the relevant parameters is given in Table 2.1. Please note that the figures in our example are chosen for didactic purposes. We believe that a numerical example is better suited to convey the main idea than purely algebraic formulae.

Table 2.1 Assumed costs and benefits resulting from certification by different control bodies (CBs).

		Rigorous CB	Easy-going CB
Private cost (certification fee)	c_P	**50**	**40**
External benefit	b_E	**20**	–
Private benefit (non-committed operator)	b_{Pi}	**5** (value of extension minus *additional* compliance cost)	**10** (value of extension)
Private benefit (committed operator)	b_{Pj}	**30** (value of extension and good feeling of supporting a committed CB)	**5** (value of extension)

Transferring the assumed costs and benefits into a payoff matrix leads to Table 2.2. This table indicates the individual payoff given the choice between a rigorous CB and an easy-going one for both types of operators, non-committed operators (denoted *i*) and committed operators (denoted *j*). Instructions for reading the table are given at the bottom of Table 2.2.

Table 2.2 Payoff matrix (i.e., net benefits) for varying numbers of committed operators and three non-committed organic operators based on their choice of different CBs.

Net benefits of …		Number of non-committed operators other than *i* choosing an easy-going CB											
		0				1				2			
Committed operator *j* choosing…		rigorous CB		easy-going CB		rigorous CB		easy-going CB		rigorous CB		easy-going CB	
Non-committed operator *i* choosing…	rigorous CB	**15**[a]	**40**[b]	15[a]	25[b]	-5[a]	20[b]	-5[a]	5[b]	-25[a]	0[b]	-25[a]	-15[b]
	easy-going CB	10	20	10	5	-10	0	-10	-15	-30	-20	-30	-35

[a] Benefit of non-committed operator *i*; [b] Benefit of committed operator *j*.
Example that gives instructions on how to read the data in the table: If
- the committed operator *j* chooses a rigorous CB, and,
- the non-committed operator *i* chooses a rigorous CB, and,
- the number of non-committed operators other than *i* choosing an easy-going CB is 0,
then
- the net benefit for the non-committed operator *i* is 15, and
- the net benefit for the committed operator *j* is 40.
This is the dominant solution because
- if the committed operator *j* is choosing an easy-going CB given that the non-committed one sticks to his choice,
  he is worse off,
- if the non-committed operator *i* is choosing an easy-going CB given that the committed one sticks to his choice,
  he is worse off, and
- equally, if both operators chose an easy-going CB, they are both worse off compared to the original situation

Payoffs resulting from costs and benefits given in Table 2.1

Note that under the assumptions of Table 2.1, all operators choose the rigorous body. Given that all other non-committed operators chose the rigorous CB, it is beneficial for the last non-committed operator to choose this CB. Furthermore, we assume that fees are independent of the number of clients. All operators wish to remain organic because the corresponding advantages (including subsidies) are thought to compensate for higher production and transaction costs (i.e., costs related to the exchange of a good (Williamson, 1985)) as compared with conventional farming. These assumptions lead to the payoff matrix presented in Table 2.2.

Because choosing a rigorous CB is the dominant strategy (Liebi, 2002; Varian, 2002) for both kinds of operators, the equilibrium produced is characterised by the bold net benefits presented in Table 2.2. In this case, the easy-going CB disappears from the market, and the opportunistic non-committed operators choose the rigorous CB because their individual gains in additional shared reputation outweigh the resulting higher fees and compliance costs. If, ceteris paribus, the private benefit of the committed operator was set to zero for both kinds of CBs in the equilibrium (perhaps because the committed operator needs no implicit extension services and has no additional "good feeling", as defined above), all committed operators would opt for the easy-going body, while the non-committed operators would remain with the rigorous CB. This situation would not affect the collective organic reputation because, by definition, committed producers always comply with the standard, regardless of how they are monitored.

Table 2.3 shows the resulting net benefits using the parameter values in Table 2.1, except for the fee of the easy-going body, which is lowered to 30 instead of 40 monetary units and thus less than the rigorous body's fee.

Table 2.3 Payoff matrix (i.e., net benefits) for varying numbers of committed operators and three non-committed organic operators depending on the choice of different CBs.

Net benefits of …		Number of non-committed operators other than *i* choosing an easy-going CB											
		0				1				2			
Committed operator *j* choosing …		rigorous CB		easy-going CB		rigorous CB		easy-going CB		rigorous CB		easy-going CB	
Non-committed operator *i* choosing…	rigorous CB	15[a]	40[b]	15[a]	35[b]	-5[a]	20[b]	-5[a]	15[b]	-25[a]	0[b]	-25[a]	-5[b]
	easy-going CB	**20**	**20**	20	15	**0**	**0**	0	-5	**-20**	**-20**	-20	-25

[a] Benefit of non-committed operator *i*; [b] Benefit of committed operator *j*.

Payoffs resulting from costs and benefits given in Table 2.1 except for the private cost of the easy-going CB, which here is 30 instead of 40

In this scenario, the dominant strategy for a non-committed operator is to choose the easy-going CB, regardless of how many other non-committed operators opt for this CB. The committed operators that choose the more expensive, stricter CB to ensure their collective reputation cannot prevent the non-committed operators from opting for the poor CB, which offers negligent certification at a low fee.

Whereas the committed operators cannot influence the monitoring quality experienced by their opportunistic colleagues, the latter are caught in a social dilemma. Instead of the 15 monetary units of net benefit that each non-committed operator would receive if all of them chose the rigorous CB, the equilibrium attained will make them each worse off by 20 units. If the committed operators, realising that they cannot influence the monitoring quality by CB choice, assign only a private benefit of, for example, 15 units (instead of 30) to the certification by the rigorous body, their dominant strategy would also be to elect the easy-going CB. Consequently, the strict CB would disappear from the organic control market.

In the end, all operators would choose the inexpensive CB with poor monitoring quality. In the real world, such adverse selection could make scrupulous CBs disappear completely from the market. Scandals and reputation losses due to sloppy controls might finally lead to the collapse of organic markets (Jahn et al., 2005). Tirole (1996) developed a dynamic model for the economic analysis of the collective reputation resulting from the individual reputations of present and former group members. He showed that once a collective reputation is poor because of the former behaviour of group members, this reputation tends to persist because committed behaviour only yields low individual rents.

One way out of this dilemma involves the effective supervision of the private CBs by competent public authorities (Deaton, 2004). Regarding this solution, our hypothesis is as follows. If effective supervision is performed, the monitoring behaviour of the CBs and (assuming that their clients share a similar structure) the resulting share of reported non-compliances and related sanctions should not vary significantly among different CBs. Before we quantitatively investigate this hypothesis, we discuss the framework on which we base this analysis.

2.4 Framework for analysing the supervision system

In an ideal certification system that assumes the random allocation of operators to CBs, we would expect all CBs to use the same control mechanisms and control frequencies. In such a system, there would be no difference in control behaviour among CBs. However, in reality, three main characteristics may contribute to differences in the proportion and type of non-compliances identified and the sanctions imposed by different CBs (see also Fig. 2.1):

1. The structure of the clients controlled (e.g., honest versus fraudulent clients, the type of operations, their size, socio-demographic variables, and criminal record),
2. Control characteristics (e.g., frequency and type of controls, risk-oriented selection of operators to be controlled, and quality of the control visit),
3. Rigidity of the CB when non-compliances are detected (i.e., its "attitude").

Characteristics 2 and 3 can be summarised as the so-called "market behaviour" of the CBs.

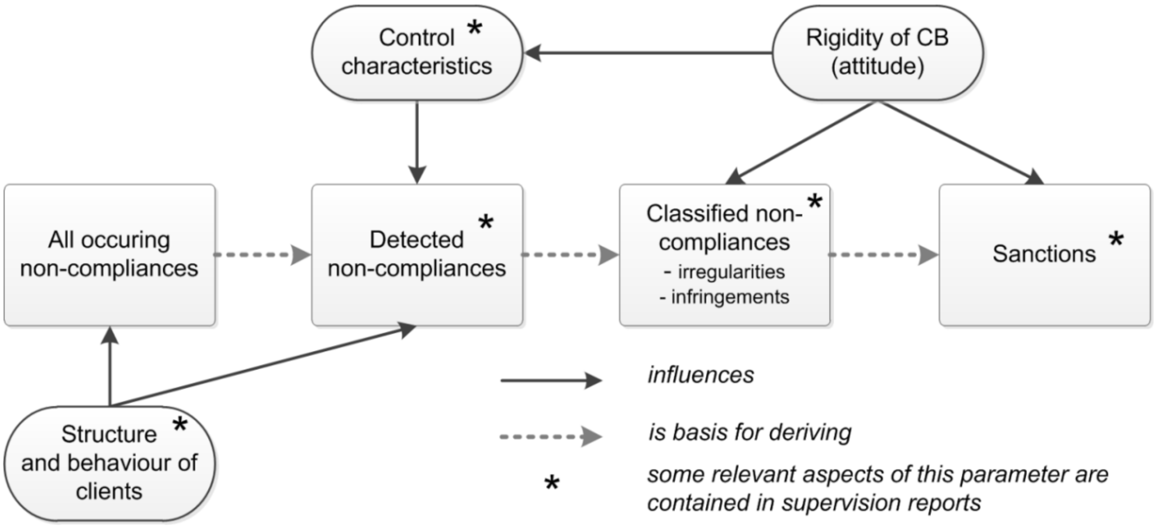

Fig. 2.1 Framework for analysing the supervision system of organic certification bodies.
Source: own graph.

The *structure and behaviour of the controlled clients* is very relevant to the number of non-compliances found (Albersmeier et al., 2009). If the assumption of a random allocation of operators is not given, a CB might have a high proportion of small farms among its clients. For example, Henson and Heasman (1998) identified firm size as key factor for compliance with new food safety regulations. In addition, a CB might have a high proportion of clients that pursue organic activities that are more prone to non-compliance than others. Clients might differ with respect to personal characteristics relevant for compliance, such as socio-demographic and psychological characteristics (Blickle, Schlegel, Fassbender, & Klein, 2006; McCarthy, O'Reilly, O'Sullivan, & Guerin, 2007 on the commitment to organic farming and compliance) and risk preferences (Halek & Eisenhauer, 2001). In general, clients could differ with respect to their organic farming activities (e.g., by belonging to different farm types such as dairy farms or arable farms). Consequently, their compliance costs as well as their future losses if they lose organic status in the event of detected non-compliance would differ. Following the general approach of the "Economics of Crime" (Becker, 1968, 1976; for an application to food safety issues see Lippert, 2002), such variations would cause differences in compliance behaviour.

The *characteristics of control visits* are often seen as highly relevant for the detection of non-compliances. It has been argued that unannounced controls result in higher detection rates (Crucefix, 2006; Rundgren, 2007). However, scientific evidence backing this common argument is lacking. Assuming a given average detection rate per control, higher control frequencies result in higher detection rates. Another aspect affecting the detection of non-compliance is the CB specific risk-based inspection approach (Houghton et al., 2008; Szajkowska, 2009), which is required by the EU regulation (Annex III, General provisions, 5.). The objective of a risk-based inspection approach is to focus resources on risky operators with regards to the frequency and intensity of controls (Alderman & Tabor, 1989; Fischer & Neuendorff, 2009 on guidelines and criteria for the implementation of risk oriented controls; Jahn et al., 2005). The structure and function of such risk-based inspection systems have not been deeply analysed (Albersmeier et al., 2009). However, CBs have different risk-based systems in place that might influence their success rate in identifying non-compliance cases. In addition, the overall quality of the control visit depends on the qualifications of the inspectors, their experience, and their level of scrutiny (Albersmeier et al., 2009).

The *attitude of a CB* can influence the judgement of an inspector during the control visit when there is room for interpretation (Albersmeier et al., 2009). Different interpretations of similar facts can result in different consequences or sanctions during the evaluation of the control report back at the CB office. Such differences in attitude (and, as a result, interpretation) are potentially quite important for the entire CB market (Jahn et al., 2005).

From a dynamic perspective, former controls and their results may influence non-compliance. A strict interpretation of an organic standard and a strict attitude resulting in rigorous sanctions for non-compliance can result in a strict reputation for a CB at a later time. Such a reputation can lead to diligent work by the operators controlled, making non-diligent operators leave or scaring fraudulent operators controlled by the CB (Eide, Rubin, & Shepherd, 2006). In this case, the CB will report fewer non-compliance cases and correspondingly fewer sanctions.

2.5 Data and research method

The data obtained from the BLE include information on all organic CBs active in Germany and their organic certification activities between 2006 and 2008 (Bundesanstalt für Landwirtschaft und Ernährung, n.d.-a, n.d.-b, n.d.-c). Information on certification activities includes the number of control visits (differentiated into announced and unannounced controls), the number of samples taken, the number of irregularities and infringements detected (as severe non-compliances), and the number of severe sanctions imposed. The data provided were generally disaggregated into types of operations (i.e., production, processing, importing, and others). However, in 2006, there was no category for "other". For this year, the non-compliances and sanctions were reported as an aggregate of all areas of operation. Note that the data only contain variables for severe non-compliance and control characteristics, but there are no structural data on the operators and no variable that could serve as a proxy for CB attitudes.

There are some obvious problems in the data. The number of severe non-compliances detected decreases considerably over the three years, from 19,329 irregularities and infringements in 2006 to 3,528 in 2007 and 1,709 in 2008. In the same period, the number of severe sanctions with financial consequences for the respective operators is relatively stable. According to regulation (EC) No. 2092/91, however, an irregularity shall result in a sanction according to Article 9, paragraph 9a, and an infringement shall result in a sanction according to Article 9, paragraph 9b. The considerable decline in the number of non-compliances in parallel with the stable level of sanctions can only be explained by a structural change in data collection methods (e.g., reporting marginal non-compliances of lower importance as compared with irregularities and infringements, especially in 2006). This change over time could be explained by incomplete definitions for irregularities and infringements.

The data can be used to test the null hypothesis that the sanction frequency between two CBs is equal. To test this hypothesis, we use the sanction frequency resulting from severe non-compliances because the data on sanctions are stable over time, whereas the non-compliance data seem to be influenced by changing definitions over time. Given an identical structure of clients, equal control frequency and accuracy, and common rigour with regards to the interpretation of the legal framework, similar results are expected across different CBs.

Because severe non-compliances occur only rarely (see Table 2.4), the observed sanction frequency (i.e., severe sanctions observed per 1,000 operators and year) of CBs with a small number of operators is very likely to randomly fluctuate much more between years than the observed sanction frequency of large CBs. To limit this effect, the data analysis is only conducted for large CBs that are characterised by more than 1,000 controlled operators. Nine CBs fulfil this criterion. These CBs represent at least 86% of operators controlled in each year.

Given the structure of the data, the potential for statistical analysis is limited. In a first step, the sanction frequency is used to compare the CBs pairwise with their control results. The method used to compare the sanction frequencies among CBs is Fisher's exact test, which allows for the comparison of small samples and small expected frequencies (Rüger, 1996; Sachs, 1984).

2.6 Results

2.6.1 Testing for differences among control bodies

The 9 large CBs included in this analysis on average imposed 3.57 severe sanctions per 1,000 operators from 2006 to 2008. Differentiating by year and CB, notable differences emerge regarding the number of sanctions imposed (e.g., see CB 3 versus CB 4 in Table 2.4). Some CBs maintain a more or less similar level of sanction frequency over time (e.g., CB 1 and CB 8), whereas others feature considerable decreases (e.g., CB 3 and CB 4) or increases (e.g., CB 5).

A simple pairwise comparison of the sanction frequencies between the large CBs reveals significant differences in every year examined, with 11 significant differences in 2006, 19 in 2007, and 21 in 2008. Over the years, 51 of the 107 comparisons (47.7%) among CBs feature significantly different sanction frequencies. Table 2.5 provides an overview of the *p*-values of all comparisons between the selected CBs from 2006 to 2008.

Table 2.4 Severe sanctions per 1,000 controlled operators (according to Article 9 of Reg. (EC) 2091/91) for 9 large CBs (own calculation, based on data from the BLE for the years 2006 to 2008).

	2006	2007	2008	average 2006-08
CB 1	6.11	6.06	4.24	**5.47**
CB 2	1.99	0.88	4.70	**2.52**
CB 3	3.05	0.00	0.00	**1.02**
CB 4	12.17	14.68	0.00	**8.95**
CB 5	3.33	6.52	12.77	**7.54**
CB 6	2.24	1.04	0.74	**1.34**
CB 7	1.38	2.04	6.23	**3.22**
CB 8	0.88	2.35	1.48	**1.57**
CB 9	3.72	7.76	3.32	**4.93**
All large CBs	**3.97**	**4.03**	**2.70**	**3.57**

Table 2.5 The p-values from pairwise comparisons of sanction frequencies between large CBs based on Fisher's exact test (own calculation, based on data from the BLE for the years 2006 to 2008). Significant values at the 0.05 level are marked in bold.

		CB 1	CB 2	CB 3	CB 4	CB 5	CB 6	CB 7	CB 8
CB 2	2006	0.138							
	2007	**0.028**							
	2008	0.347							
CB 3	2006	0.164	0.725						
	2007	**0.000**	0.304						
	2008	**0.007**	**0.003**						
CB 4	2006	**0.016**	**0.003**	**0.001**					
	2007	**0.000**	**0.000**	**0.000**					
	2008	**0.006**	**0.002**	–[a]					
CB 5	2006	0.229	0.719	1.000	**0.001**				
	2007	0.722	**0.020**	**0.000**	**0.013**				
	2008	**0.000**	**0.034**	**0.000**	**0.000**				
CB 6	2006	**0.002**	1.000	0.450	**0.000**	0.426			
	2007	**0.000**	1.000	0.133	**0.000**	**0.000**			
	2008	**0.004**	**0.004**	0.365	0.369	**0.000**			
CB 7	2006	**0.024**	1.000	0.480	**0.000**	0.311	0.758		
	2007	0.082	0.637	**0.047**	**0.000**	0.069	0.400		
	2008	**0.037**	0.797	**0.000**	**0.000**	**0.045**	**0.000**		
CB 8	2006	**0.026**	0.603	0.434	**0.000**	0.260	0.502	1.000	
	2007	0.064	1.000	0.108	**0.000**	0.055	0.643	1.000	
	2008	0.752	0.252	0.128	0.112	**0.000**	0.303	0.050	
CB 9	2006	0.389	0.706	0.766	**0.008**	1.000	0.364	0.272	0.228
	2007	0.454	**0.010**	**0.000**	0.056	0.686	**0.000**	**0.036**	**0.028**
	2008	0.610	0.549	**0.006**	**0.004**	**0.002**	**0.009**	0.232	0.479

[a] *both CBs did not report any sanction in this year*

When testing many hypotheses with a specified Type I error probability (in this case, 5%), multiple testing problems occur. With the number of hypotheses tested, the probability increases that "at least some Type I errors are committed" (Shaffer, 1995). The unweighted Bonferroni method suggests that the significance level must be divided by the number of tests (here, 36 pairwise comparisons per year) to derive a multiple significance level. Under the assumption of a true null hypothesis (i.e., there are no differences among the CBs) and for an overall error probability of 5%, this results in an adapted significance level of 0.0014. At this level, at least 23 results (21.5% of all comparisons) with p-values of 0.000 are still significantly different.

Our analysis of the data collected on supervision shows that in the German organic control system, significantly different control results exist among CBs from 2006 to 2008. This leads us to question which factors could explain these differences.

2.6.2 Explaining the identified differences in sanction frequencies

The data available provide information on only some of the factors identified in chapter 2.4 (see Fig. 2.1). Factors that could be related to the differences among CBs that are covered by the data include the structure of the clients (i.e., number of farmers, processors, importers, and others – that is the area of production), control characteristics (i.e., control frequency and the number of announced and unannounced controls), and the sanction frequency. In Table 2.6, these data are compiled and compared for a selection of notable CBs that either sanction much more than the other CBs or much less.

The average number of severe sanctions in Table 2.6 is based on the same information as in Table 2.4, but in a different format. This is the variable that we would like to explain. However, given the few cases we have, a formal statistical analysis is only possible at a rudimentary level. It would be desirable to have additional variables and more disaggregated data. Nevertheless, we present the available data and add tentative discussion of possible inferences.

The first factor that may explain different sanction frequencies is the control frequency (i.e., the average number of controls per operator and year). During the period of analysis, those CBs that imposed significantly more sanctions (i.e., CB 4 and CB 5) showed a lower control frequency than the other CBs. This result does not support the conventional assumption that more control visits lead to higher detection rates, indicating that there may be unobserved intervening factors.

Table 2.6 Determinants that could explain differences in control results between the most extreme CBs with regards to sanction frequency (ordered by decreasing sanction frequency; own calculations, based on data from the BLE for the years 2006 to 2008).

	Number of severe sanctions per 1,000 operators				Number of controls peroperator				Share (%) of unannounced controls				Share of farm operators in all controlled operations			
	2006	2007	2008	**Ø 2006-08**	2006	2007	2008	**Ø 2006-08**	2006	2007	2008	**Ø 2006-08**	2006	2007	2008	**Ø 2006-08**
CB 4	12.2	14.7	0.0	**8.9**	1.16	1.06	0.99	**1.07**	15	1	2	**6**	80	76	75	**77**
CB 5	3.3	6.5	12.8	**7.5**	1.09	1.13	1.11	**1.11**	11	10	10	**10**	75	73	71	**73**
CB 6	2.2	1.0	0.7	**1.3**	1.14	1.20	1.13	**1.15**	12	11	12	**11**	69	64	63	**65**
CB 3	3.1	0.0	0.0	**1.0**	1.10	1.28	1.30	**1.23**	6	15	14	**12**	46	36	40	**41**
All nine large CBs	4.0	4.0	2.7	**3.6**	1.14	1.16	1.14	**1.15**	12	10	12	**12**	68	64	63	**65**

Second, analysis of the share of unannounced control visits among all controls reveals that the CBs that imposed significantly more sanctions than others performed unannounced controls less often than other CBs did. Again, this result does not support the widespread argument that unannounced control visits are an effective instrument to ensure organic integrity.

Third, turning to the structure of CB clients, the area of production must be compared with respect to the ratio between the share of sanctions imposed and the share of operators (i.e., the share of sanctions in relation to the share of operators). During 2007 and 2008, farm operators and especially importers were sanctioned relatively frequently, whereas processors and other types of operators were sanctioned relatively rarely. The overall share of importers is relatively small; accordingly, the share of farm operators is more influential. The share of farmers controlled is above the average for the CBs that sanctioned more frequently.

The analysis of these three factors is backed by a correlation analysis based on Kendall's tau. Significant correlations between these factors and the sanction frequency were not detected. Strictly speaking, this means that the hypothesis of a relationship between the explanatory variables and the sanction frequency must be rejected. Therefore, the variables investigated do not contribute to explaining the differences in sanction frequencies. However, the high aggregation level of the data and other factors discussed above (not reflected in the data) might be important for this result. As such, both explanations deserve closer attention.

2.7 Discussion

The data analysis shows that these official data are not sufficient to fully assess the European organic control system. The data were useful for assessing the fulfilment of some minimum requirements, such as the number of controls, and it was also possible to use the data to assess whether large CBs act differently with respect to sanction frequency. However, the data were not suitable for assessing why the sampled CBs were different. This is a major shortcoming given the possibility of adverse selection.

The data suffered from problems such as missing definitions of key terms (particularly "infringement" and "irregularity"), and the non-compliance data seemed to be affected by changing variable definitions over time.

When discussing the results of this analysis with CBs and representatives from the involved authorities, it became apparent that some CBs did not report all sanctions for the operators they controlled to the BLE; some sanctions (i.e., those according to Reg. (EC) No. 29092/91, Article 9(9)b) were imposed by the competent authorities. The CBs argued that these sanctions were known by the organic system administration (on the Länder level), and thus, they did not need to report them to the BLE (federal level), which collects data for supervision. This might be a specific German problem resulting from the federal organisation of the control system that could easily be alleviated by instructing the CBs accordingly, as has been done recently. Supervision at the European level would be severely hindered if the most severe sanctions are only partially reported.

When we compared the official data reported to the European Commission with the primary data from one of the nine large CBs, differences became evident because of false reporting in the year 2008. The false reporting was quite obvious but went unnoticed by both the CB and the BLE. It appears that not all opportunities to verify and correct the provided data were used.

2.8 Conclusion

Our analysis shows that the data collected are not sufficient to explain the differences revealed among CBs. Unfortunately, these data do not cover important factors that may affect the control results. Specifically, little is known about the controlled operators. A future line of research could be based on data from individual operators, which are available only from CBs. Such research could contribute to a better understanding of the feasibility and usefulness of adding data to supervision reporting.

At the European level, it seems important to clearly define the central terms of the organic regulation. Similarly, elements of training and organised communication among competent authorities at the European level could contribute to fewer differences in the implementation of the organic regulation.

Generally, the use of the supervision reports seems to be limited, possibly because of the data structure and quality. The motivation of CBs to provide data could be improved if they realised that the data are actually used.

Based on the available reports, we cannot reject the hypothesis that there are significant differences in the attitudes and rigour of German organic farming CBs, which could lead to adverse selection in the long run.

This case study on German data highlights elementary shortcomings in the supervision quality of organic certification. The implementation of a sophisticated supervision of organic control systems at the national and European levels requires resources, especially initially. Despite the costs, this investment is essential for building consumer trust in the growing organic market.

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3 An analysis of the risks of non-compliance with the European organic standard: a categorical analysis of farm data from a German control body[1]

Authors: Alexander Zorn, Christian Lippert, Stephan Dabbert

Abstract: This paper quantitatively analyses the risk of non-compliance with European regulations on organic farming in Germany. Based on the economics of crime, we derive hypotheses regarding the factors that are expected to influence non-compliance. We use a data set from an important organic control body that contains farm and control data for the period from 2007 to 2009. Ordinal logistic regression models are used to test our hypotheses. The following characteristics of organic farms significantly increase the probability of non-compliance: short organic farming experience, farm size and the existence of conversion area.

Keywords: Organic farming, economics of crime, non-compliance, risk-based controls, ordinal logistic regression model.

JEL classifications: Q12, K42, C25

Acknowledgements: This article was generated 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. The article reflects the views of the authors 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. The authors thank Danilo Gambelli, Francesco Solfanelli and Raffaele Zanoli for helpful comments on an earlier version of this article. All remaining errors and mistakes are ours.

[1] This chapter consists of an unpublished manuscript that has been submitted to a scientific journal.

3.1 Introduction

Organic farmers in Europe are subject to the European organic regulation (Council Regulation (EC) No 834/2007 on organic production and labelling of organic products). This regulation specifies the production rules for organic operators and the basic control procedures that operators (i.e., farmers, processors, retailers, and importers) undergo. According to the European organic regulation, the control frequencies of individual operators should result from the '*risk of occurrence of irregularities and infringements*' (Art. 27 (3) of the European organic regulation)[2]. In the context of organic food quality, a risky operator is an operator that has a relatively high probability of severe non-compliance with the organic regulation, and this level of non-compliance affects a product's organic integrity. The above-mentioned Article 27 refers to the concept of risk-based controls; this concept is ubiquitous in debates regarding the quality and further development of food control systems. Generally, risk-based control systems enhance the effectiveness and efficiency of controls by prioritising and directing resources toward relatively risky operators (Jahn *et al.*, 2005; Albersmeier *et al.*, 2009).

In this article, we estimate the probabilities of sanctions by employing an ordinal logistic regression model that uses data that were collected by a German organic control body (CB) for farms between 2007 and 2009. Extending the qualitative risk classification, that is currently applied by some CBs, to a quantitative approach using categorical data analysis can contribute to enhancing the concept of organic risk-based controls. In this way, the organic control system in Europe could be improved with more effective and efficient controls.

The following section provides an overview of the literature on risk-based approaches in food inspection schemes. Section 3.3 introduces the theory underlying the following statistical analyses and the derived hypotheses. Section 3.4 illustrates and describes the methodology and data that are employed in this study. Finally, section 3.5 presents the results and related discussion.

[2] The European organic regulation relates the term 'risk' to the '*risk of occurrence of irregularities and infringements*' without providing a detailed definition. However, the sanctions following from an irregularity – '*the control body shall ensure that no reference to the organic production method is made in the labelling*' – and an infringement – '*the control body shall prohibit the operator concerned from marketing products which refer to the organic production method*' (Art. 30 (1) of the European organic regulation) – suggest a limitation of risk-based inspections to severe non-compliance.

3.2 Literature review

Food safety risks and risk-based control approaches in general have been described and analysed by international organisations (Food and Agriculture Organization of the United Nations, 2006; Codex Alimentarius Commission, 2011) and in the scientific literature (Jahn *et al.*, 2005; Albersmeier *et al.*, 2009; Hoffmann, 2010). Research that specifically examines the implementation of risk-based control systems in organic certification is sparse (Jahn *et al.*, 2005; Schulze *et al.*, 2008; Fischer and Neuendorff, 2009). However, a number of articles highlight the relevance and expected efficiency gains from risk-based food control systems for the organic sector. An interesting source on the topic is the international professional journal on organic certification, *The Organic Standard*, in which some articles on organic risk-based controls have been published. Rundgren (2004) noted that risk-based control approaches had previously been practised in organic certification. These approaches had to be terminated as a result of the standardisation of inspection procedures and regulatory requirements. In recent years, different European organic control bodies have accumulated experience with risk-based approaches (TOS, 2006). Recently, Rundgren highlighted the requirement of risk-based controls in the European organic regulation, but he concluded that there has been '*little progress on this to date*' (Rundgren, 2010). A German handbook for control bodies suggests a procedure for a risk-based control approach: operations can be categorised into three risk classes according to seven parameters (Fischer and Neuendorff, 2009).

As a result of contacts with the organic certification sector, we conclude that control bodies currently apply simple quantitative methods in combination with qualitative assessments to categorise operators into risk classes (Fischer and Neuendorff, 2009; Piva, 2010; Rundgren, 2010). These simple approaches have the advantage of being cost-efficient, comprehensible, and easily realisable. When examining food quality certification in general, Albersmeier *et al.* (2010) refer to financial auditing and suggest an adapted audit risk approach. These authors indicate the importance of the analysis of control data and suggest a central database to monitor the certification system at the 'standard owner' level. European organic control bodies collect and store a substantial amount of data pertaining to their operators, control visits, and non-compliance and sanctions. These data create the potential for sophisticated quantitative risk analysis approaches. To our knowledge, this potential has not yet been exploited in the scientific literature or by the control bodies themselves.

3.3 Theory and derived hypotheses

The *economics of crime* approach indicates that opportunistic individuals consciously choose whether to comply with a law based on rational decisions: an opportunistic individual compares the total pay-offs of these two alternatives (Eide, 2000). The credence characteristic of organic food leaves room for opportunism and cheating, as buyers of organic products cannot verify the organic quality (Ward *et al.*, 2004). Adapting Becker's model on the supply of offences (Becker, 1968) to organic farming, one could argue that non-compliance with an organic standard by a rational operator is determined by the income that results from non-compliance, the detection probability, and the penalty in case of a sanction. Moreover, time preference can be an influential factor in the decision of whether to comply[3]. Farm characteristics constitute the focus of our analysis, as these characteristics are important determinants of farm income. Factors that influence farm income include compliance costs, quantity produced, and price obtained.

Complying with an organic standard is costly: generally, one must be informed about the rules of an organic standard. The guidelines of organic standards usually constrain the application of certain inputs or methods, and such constraints result in higher production costs (Ward *et al.*, 2004). Harvest yields are usually lower in organic farming. Organic food prices generally exceed conventional food prices (Mäder *et al.*, 2002). The opportunities for manipulation during production, processing, and marketing are manifold (Giannakas, 2002) and may be associated with varying degrees of intention from laxness to severe fraud. Laxness can be understood as a behaviour that reduces the costs of compliance and thus only differs from intentional fraud in terms of degrees. Finally, the personalities of farmers and their employees may also influence farm income. Personal traits and preferences are related to a person's risk aversion, which is particularly relevant for the propensity to behave opportunistically. This summary of information constitutes the theoretical framework on which the following hypotheses are based.

[3] It is important to consider situations in which actions occur in the 'self-enforcing range' (Klein, 1985). Such a situation occurs when the discounted future income losses resulting from fraud and its detection exceed the short-term profit from cheating.

Fundamentally, compliance costs, risk behaviour, and farm income depend on farm and farmer characteristics. A farmer's age may have an influence that results from age-based differences in risk aversion (Halek and Eisenhauer, 2001). Sex may also have an effect; studies revealed that women are more averse to risk (e.g., Eckel and Grossman, 2002). We expect that experienced organic farmers have higher compliance rates than inexperienced farmers for two reasons. First, the information and compliance costs of inexperienced farmers are higher as a direct result of their lack of experience. Second, we attribute a greater commitment to organic farming and its standards to experienced farmers (McCarthy *et al.*, 2007; Best, 2008)[4]. Furthermore, the existence of long-term trade relationships and the costly development of a valuable reputation, which would be lost in situations in which opportunism is detected, could contribute to higher compliance rates. The affiliation of a farm with an organic federation and its adherence to the stricter additional standards of such federations is another proxy for commitment to organic farming rules. Such an affiliation could also affect compliance rates because of social control aspects that entail a higher detection probability for non-compliance cases.

Henson and Heasman (1998) identified the size of an operation as a key factor for compliance with food safety regulations. They concluded that '*large firms are generally more able to comply*'. Economies of scale in quality management activities (Holleran *et al.*, 1999) may matter in this context. Moreover, better compliance of large firms could result from relatively higher incomes at stake. Finally, the location of farms may affect compliance rates: natural conditions determine potential agricultural production (e.g., low site or soil quality only allows for extensive production methods with fewer inputs). Hence, extensive production may be accompanied by higher compliance rates. In Germany, there is a negative correlation between soil quality and the share of organically farmed land (Schmidtner *et al.*, in press). A higher share of organic farms may have positive effects on the information that farmers possess and increased social control effects, both of which result in a higher compliance rate. A farmer's personal financial situation and that of his farm could also influence his compliance behaviour: higher liquidity is associated with lower time preference that leads to a higher compliance rate. In other words, when a farmer has serious liquidity problems, he will be more inclined to cheat because he must earn money immediately.

[4] These hypotheses are similarly relevant for the characteristics of employed farm workers.

Farm products can have diverse influences on compliance. Information and compliance costs can differ among various products because, for example, various types of crops are regulated differently (amount, level of detail, and complexity of rules). Marketability and prices differ across crops and different points in time. These factors may influence the likelihood of cheating. Production intensity can be an important factor with regard to compliance: in organic farming, many agricultural production inputs that are common in conventional agriculture cannot be used. The abandonment of conventional inputs usually results in lower yields and can lead to higher production costs. This aspect is especially relevant for intensive forms of agricultural production, such as fruit and vegetable production. Intensive organic production is usually more challenging because of difficult production conditions (e.g., more prone to illness, higher nutrition demands, or more labour intensive). In intensive areas of crop production (e.g., fruit growing or vegetable gardening) and husbandry (e.g., pigs or poultry), we expect lower compliance rates. In contrast, higher compliance rates are expected in extensive areas with fewer products traded within markets, such as pasture, set-aside areas, and sheep and goat husbandry. The existence of additional processing activities on a farm increases operational complexity and could therefore also contribute to higher non-compliance rates. The effects of crop and livestock production on compliance can vary between years because of seasonal production difficulties and market developments that may affect farm production and liquidity.

Sanctions and corrective measures in previous years may have both a learning effect and a deterrence effect. However, prior sanctions could also indicate that a farmer has been particularly prone to non-compliance because of limited skills or careless attitudes that translate into higher compliance costs. Therefore, we hypothesise that previously observed non-compliance may decrease or increase the current sanction probability. For an overview on the factors hypothesised to affect non-compliance, the available proxy variables and their direction of action, see Table 3.1.

Table 3.1 Factors that are hypothesised to influence non-compliance, the direction of influence expected, and available proxy variable(s)

Factor	Proxy variable(s)	Hypothesised influence on non-compliance
Overall characteristics of farms and farmers		
A farmer's personal characteristics, such as time preference, age, sex, risk aversion, and reputation	Lagged sanctions	↗ ↘
Organic farming and control experience	Control contract duration with current CB	↘
Commitment to organic principles	Number of other certification schemes; Control contract duration with current CB	↘ ↘
Social control aspects	Number of other certification schemes	↘
Farm size	Farmed area (in km²)	↘
Parallel production	Conventional area; Conversion area	↗ ↗
Complexity of business operation	Farm is controlled for processing activity; Dummies for animal husbandry	↗ ↗
Sanctions in previous years	Lagged sanctions	↘ (learning effect)
Farm location (natural conditions and proximity to other organic farms)	– (no suitable proxy variables included in the data set)	
Farm production characteristics		
Intensive crop production	Crop dummies for • Fresh vegetables • Fruits including wine grapes	 ↗ ↗
Extensive crop production	Crop dummies for • Unutilised and/or fallow land • Permanent grassland • Green fodder from arable land • Dried pulses	 ↘ ↘ ↘ ↘
Intensive husbandry	Livestock dummies for • Poultry husbandry • Pig husbandry	 ↗ ↗
Extensive husbandry	Livestock dummy for • Sheep and/or goat husbandry	 ↘

Notes: ↘ - decreasing effect on non-compliance; ↗ - increasing effect on non-compliance.

In this paper, we focus on the effects of farm characteristics on compliance. Other factors that may influence the detection of non-compliance, such as the interpretation of the regulation by the supervising authority, the rigidity of a specific inspector or the type of control (e.g., it is generally assumed that unannounced controls lead to higher detection rates) are not considered in this study.

3.4 Methodology and data

Adapting the definition of risk from the *Codex Alimentarius Commission* (related to food safety) to the context of organic food integrity, we defined risk as a function of the probability of an adverse effect on organic integrity and the severity of this effect (Codex Alimentarius Commission, 2011). We used the sanction that is imposed on an operator as a proxy for risk. The sanction levels that are defined in Germany reflect the severity of the underlying non-compliance.

Preliminary analyses for the models were conducted using bivariate analyses based on contingency tables and adequate independence tests (G-test and Fisher's exact test) (Hosmer and Lemeshow, 2000). Furthermore, the potential independent variables to be used in the models were checked for multicollinearity (Chatterjee *et al.*, 2000). Multicollinearity is a relevant concern because certain types of agricultural production tend to be linked to one another (e.g., grassland farming to dairy production).

The dependent variable in our analysis is the type of sanction that is issued to operators. We have different categories of sanctions in our data (i.e., sanction is a categorical variable). Different regression models use the available data to specific degrees. A logistic regression model can be used to explain binary outcomes; thus, in our example, we would model whether an operator was sanctioned. This model is appropriate to explain the sanction probability globally without regard for the severity of a sanction (Urban, 1993; Long and Freese, 2006).

An ordinal logistic regression model also considers the severity of a sanction. Compared with a binary logistic model, an ordinal logistic regression model uses the information that is provided by the sanction data more comprehensively. Because of the ordered character of the sanction categories in our data set, such a model can be applied. The ordinal logistic regression model is based on the assumption of parallel regressions (i.e., the slope coefficients for different outcomes of the dependent variable are identical). This modelling approach implicitly assumes that different sanction categories identically depend on the same influencing factors. This parallel regression assumption is frequently violated in practical applications (Urban, 1993; Long and Freese, 2006).

We utilised data for three calendar years (i.e., 2007, 2008, and 2009) for which we estimated three separate cross-sectional ordinal logit models. The risk of non-compliance was approximated by the most severe sanction[5] imposed. The seven distinct sanction categories in the German organic control system are structured hierarchically and hence can be considered ordinal variables (Agresti, 2002). The rare occurrence of severe sanctions can result in estimation problems in the absence of variation between the dependent and independent variables. Therefore, the seven sanction categories were grouped into three classes of sanction severity that were used as dependent variables in the models.

The ordinal logistic regression model is based on the structural equation of the binary logit model (Long and Freese, 2006): to model the general risk of a sanction, we assume a latent or unobserved dependent variable $y*$ with $-\infty < y* < +\infty$ that is associated with the independent variable x through the following equation:

$$y_i^* = x_i \beta + \varepsilon_i \tag{3.1}$$

where

y_i*	is the latent dependent variable for observation i,
x_i	is the row vector of independent variables for observation i,
β	is the column vector of coefficients to be estimated, and
ε_i	is the random error of observation i.

The latent variable y_i* is associated with the observed variable y through the following equation:

$$y_i^* = \begin{cases} 1 & if\, y_i^* > 0 \\ 0 & if\, y_i^* \leq 0 \end{cases} \tag{3.2}$$

The difference between the binary logit and ordinal logistic models is that for the latter the observed variable y is a polytomous variable: in our study, the observed variable is given by the most severe sanction that is imposed on a farm operation in a specific year and includes '*no sanction imposed*' ($j = 0$) and the seven following gradual sanction categories that we merged into three additional categories:

5 This variable is defined by the most severe sanction category that may be imposed on a farm. The frequency of such a sanction is not relevant.

- written indication (*j = 1*);
- explicit documentation and obligatory information (*j = 1*);
- sanctioned control visit (*j = 1*);
- warning (*j = 2*);
- provisional prohibition of organic marketing due to suspicion (*j = 3*);
- prohibition of organic marketing related to individual batches (*j = 3*);
- prohibition of organic marketing in general for a certain period of time (*j = 3*).

Thus, the measurement model for the $J = 4$ ($j = 0, \ldots, 3$) ordinal outcomes is as follows:

$$y_i = m \quad \text{if}\, \tau_{m-1} \leq y_i^* \leq \tau_m \quad \text{with}\, m = 1\; to\; J\,. \tag{3.3}$$

with *J-1* cutpoints or thresholds τ_1 to τ_{J-1} to be estimated and delineating the sanction categories. The probability of observing $y = m$ for a given x is defined as follows:

$$\Pr\ (y = m\,|x\,) = \Pr\ (\tau_{m-1} \leq y^* \leq \tau_m \mid \mathrm{x}). \tag{3.4}$$

Hence, the general formula for the predicted probability in the ordinal regression model can be derived as follows:

$$\Pr\ (y = m\,|x\,) = F\ (\tau_m - x\beta) - F\ (\tau_{m-1} - x\beta), \tag{3.5}$$

with the cumulative density function F for ε (Long and Freese, 2006).

For every year considered, the modelling began with the estimation of an unrestricted model. Subsequently, a restricted estimation via a backwards stepwise procedure at the p=0.1 level was performed. If a strongly correlated variable was part of the restricted model, then the effect of the correlation was tested by excluding the corresponding variable from the estimation. The final restricted model was estimated via backwards stepwise procedure at the p=0.05 level. For the evaluation and comparison of the resulting models, we referred to the likelihood ratio test (LR test), McFadden's R^2 (Pseudo-R^2), and the Bayesian information criterion (BIC).

The data that were used in the analysis were obtained from the database of a major German organic control body. The data cover the years from 2007 to 2009. Because of differences in data recording and to ensure consistent measurement, especially regarding lagged variables, we used data only for farms that were active in all three years of the analysis. This approach results in a balanced panel data set. The data set consists of 1,421 farms for each year and yields a total of 4,263 observations. During an average year, 47% of the farms were sanctioned (see Table 3.2 below).

Table 3.2 Share of farms (in %) by the most severe sanction* imposed, 2007 – 2009 and totals

Grouped sanction by severity	Year 2007	2008	2009	Totals
No sanction	50.04	53.48	56.65	53.39
Grouped sanction 1	45.11	42.43	39.06	42.20
Grouped sanction 2	2.60	2.60	3.38	2.86
Grouped sanction 3	2.25	1.48	0.91	1.55

Notes: * The variable 'Most severe sanction imposed' ranges from 0 to 3 and is given by the most severe of the grouped gradual sanction categories (cf. above). Number of farms in each year: 1,421.

The distribution of the sanctions by severity reflects the gradual character of the sanction structure in Germany's organic control system: slight sanctions (grouped sanction 1), such as written indications or obligations to improve documentation or to better inform the control body, account for approximately 90% of all sanctions. Severe sanctions (grouped sanction 3), such as (provisional) prohibitions on marketing products as organic and those that involve considerable potential financial consequences for farms, were rarely imposed. The share of severely sanctioned farmers decreased considerably over the period under consideration.

Table 3.3 provides an overview of the dependent and independent variables that were used in the models. The displayed means of the crop and livestock variables (in the form of dummy variables) provide the share of farmers cultivating a corresponding crop or raising a respective livestock type. Due to the balanced data set, most variables do not vary considerably over the years under investigation.

Table 3.3 Summary statistics (means and standard deviations) of the variables that were used in the models for the period from 2007 to 2009 (n=1,421 in each year)

Variable	Mean 2007	Std. Dev.	Mean 2008	Std. Dev.	Mean 2009	Std. Dev.
Most severe sanction imposed (from 0 to 3)	0.584	0.715	0.529	0.664	0.492	0.641
Control contract duration (in decades)	0.737	0.354	0.837	0.354	0.937	0.354
Number of other certification schemes [1]	0.875	0.402	0.875	0.402	0.875	0.402
Farmed area (in square kilometres)	0.430	0.851	0.427	0.804	0.434	0.796
Conventional area [2]	0.005	0.070	0.005	0.070	0.005	0.070
Conversion area [2]	0.336	0.472	0.343	0.475	0.341	0.474
Cereals [2]	0.526	0.499	0.545	0.498	0.548	0.498
Dried pulses [2]	0.110	0.313	0.125	0.330	0.129	0.335
Root crops [2]	0.155	0.362	0.157	0.364	0.164	0.370
Industrial crops [2]	0.172	0.378	0.117	0.321	0.113	0.317
Fresh vegetables [2]	0.213	0.409	0.202	0.402	0.194	0.396
Green fodder from arable land [2]	0.526	0.500	0.506	0.500	0.512	0.500
Other arable land crops [2]	0.027	0.161	0.023	0.148	0.023	0.148
Permanent grassland [2]	0.871	0.335	0.875	0.331	0.872	0.334
Fruits (incl. wine grapes) [2]	0.063	0.242	0.061	0.240	0.065	0.246
Unutilised and/or fallow land [2]	0.148	0.355	0.218	0.413	0.287	0.453
Other and/or unknown crops [2]	0.095	0.293	0.061	0.240	0.059	0.236
Bovine husbandry [2]	0.526	0.500	0.529	0.499	0.514	0.500
Pig husbandry [2]	0.146	0.354	0.150	0.357	0.106	0.308
Sheep and/or goat husbandry [2]	0.116	0.320	0.121	0.326	0.070	0.256
Poultry husbandry [2]	0.207	0.405	0.217	0.412	0.127	0.333
Farm is controlled for processing activity [2]	0.061	0.240	0.068	0.252	0.070	0.256

Notes: [1] Other certification schemes refer to other organic certification schemes apart from the EU organic standard (e.g., certification under private standards, such as Demeter or Bioland).
[2] A dummy variable equal to 1 indicates that the attribute is present.

3.5 Results and discussion

The ordinal logistic regression models were calculated through maximum likelihood estimation using *Stata 11*. Table 3.4 presents the results of the yearly models and of the lagged models for 2008 and 2009. The latter models include a lagged sanction variable that represents the imposition and severity of a sanction in the previous year; all other data represent the year that is indicated.

The upper portion of Table 3.4 shows the estimation characteristics. McFadden's R^2 values are usually smaller than R^2 values in an ordinary least squares model (Hosmer and Lemeshow, 2000). However, the values in our models are small (all values are below 0.1); this result indicates limited explanatory power. The LR test results for the restricted models demonstrate that the coefficients of the models are significantly different from zero. The BIC can be used to compare nested models (Long and Freese, 2006). The inclusion of sanctions in the previous year in the models induced a considerable increase in the McFadden's R^2 values for both of the corresponding models, whereas the BICs only slightly decreased, as the BICs also reflect the increased number of independent variables.

Table 3.4 Model results of yearly models and lagged models for 2008 and 2009 (n=1,421 for each model)

Model characteristics	2007	2008	2009	2008 lagged	2009 lagged
McFadden's R^2	0.0437	0.0327	0.0596	0.0541	0.0720
Likelihood ratio test	0.0000	0.0000	0.0000	0.0000	0.0000
Bayesian information criterion	-7820	-7905	-7973	-7957	-8003
Variable	*Estimated coefficients and significance level*				
Control contract duration	-0.436 [b]	-0.598 [c]	-0.320 [a]	-0.463 [b]	
Farmed area	0.166 [a]	0.329 [c]	0.185 [b]	0.287 [c]	0.133 [a]
Conversion area [1]	0.400 [c]	0.411 [c]	0.858 [c]	0.377 [b]	0.813 [c]
Root crops [1]			0.363 [a]		0.363 [a]
Industrial crops [1]	0.394 [b]				
Green fodder from arable land [1]	-0.268 [a]				
Other arable land crops [1]	1.500 [c]	1.034 [b]			
Permanent grassland [1]			-0.585 [b]		-0.586 [b]
Unutilised and/or fallow land [1]	0.383 [a]				
Bovine husbandry [1]	0.627 [c]		0.450 [c]		0.448 [c]
Pig husbandry [1]			0.455 [a]		0.408 [a]
Poultry husbandry [1]		0.472 [c]	0.724 [c]	0.439 [c]	0.609 [c]
Farm is controlled for processing activity [1]	0.505 [a]				
Lagged sanctions [2]				0.640 [c]	0.519 [c]

Notes: [a] $p<0.05$, [b] $p<0.01$, [c] $p<0.001$.
[1] A dummy variable equal to 1 indicates that the attribute is present.
[2] Lagged sanctions equal the most severe sanction that is imposed on a farm in the previous year and may range from 0 (no sanction) to 3 (severe sanction).

The ordinal logistic regression model is based on the parallel regression assumption (also known as the proportional odds assumption). This assumption was rejected for the 2007 model but was not rejected for any of the other models based on the Wald test that is suggested by Brant (Long, 1997). The Brant test facilitates global testing of the equality of the coefficients and that of individual variables. The violation of the parallel regression assumption for the 2007 model can be explained by the absence of any medium sanctions observed in our data for the 'processing activity' variable in that year[6]. Interestingly, different sanction categories can be explained by the same variables, as the parallel regression assumption was violated only once because of a vacant sanction class.

Discussion

The estimated coefficients cannot be directly interpreted and compared with one another. Therefore, we first consider the directions that are indicated by the algebraic signs: negative coefficients indicate a decreasing effect on the probability of sanctions, and positive coefficients indicate an increasing effect.

The results of the five cross-sectional models support one another in the sense that no contradictory effects were discovered based on the direction of the signs. Some variables do not significantly contribute to the sanction probability. Several coefficients are significant only in a single year. This result is especially prominent for a variety of crop variables (root crops, industrial crops, green fodder from arable land, permanent grassland, and unutilised and/or fallow land), pig husbandry, and processing activities. Some variables are repeatedly significant: this result is especially relevant for overall farm characteristics, such as organic control experience, farmed area, and the presence of conversion areas. Livestock farming (bovine and poultry), other arable land crops, and the lagged sanctions variable are also repeatedly significant.

The results of the regression models with respect to the hypotheses that we formulated in section 3.3 provide support for several hypotheses. First, according to the results, experience with organic controls clearly contributes to decreased sanction probability. However, the increasing effect of farm size on sanction probability contradicts the results that were obtained by Henson and Heasman (1998) and our respective hypothesis. The potential effect of increasing complexity (e.g., a division of labour that requires more organisation and communication) appears to be stronger. The existence of conversion areas causes sanction probability to increase, and this result is consistent with our hypothesis.

Second, we contrasted the crop production characteristics with our hypotheses and prior considerations. The decreasing effects of permanent grassland farms and farms with

[6] It is not astonishing that no medium sanction was observed because of the low number of farms with processing activities (n=87 or 6.1% of the sample) and the low number of operators on which medium sanctions were imposed (n=37 or 2.6% of the sample).

green fodder on the sanction probability are consistent with our expectations. Root crops and industrial crops have increasing effects on the sanction probability. These effects are plausible because the demands on the skills of farmers and the required agricultural activities and inputs for these crops are higher. The effects of the category ‘other arable land crops’ could not be further evaluated because of the vague definition of the included crops. The decreasing effect of farms with unutilised land on the sanction probability was surprising and can only be explained by unobserved interaction effects.

Third, three livestock categories exhibit an increasing effect on sanctions: bovine animals, pigs, and poultry. This result is plausible because the presence of livestock on a farm entails additional production rules that must be considered (e.g., regarding indoor and outdoor areas, and medication). The significant effects of poultry and pig production are consistent with our hypotheses in view of the specific challenges in these production areas.

Finally, the inclusion of lagged sanction variables resulted in highly significant, increasing effects on sanction probability. Hence, the hypothesis that there is an important learning or deterrence effect, that results from sanctions in the previous year, must be dismissed. As the control body uses present sanctions for the evaluation of non-compliance risk for future controls (see below), this important result supports the approach of the control body.

The data-providing control body uses a qualitative risk classification approach that consists of three risk classes (ranging from low (1) to high (3) risk). The risk classification is used to sample operations to determine additional future control visits. An important criterion that was used to classify the farms is the result of previous controls (especially the number and types of sanctions that were imposed). As mentioned above, the relevance of this criterion is supported by the results of the lagged models. The other criteria used for risk classification are parallel conventional production and specific risk crops (e.g., table grapes). However, these criteria were not confirmed by our statistical analyses.

To explore the differences between the qualitative and quantitative risk classifications, we analysed the correlation between the 2008 classifications (risk classification of the CB versus the estimated sanction probabilities of the unlagged model for 2008) and the sanctions that were imposed in 2009[7].

As expected, the Pearson correlation coefficient between the risk classification of the control body and the degree of sanction is highly significant and positive, although the correlation is weak (0.2189, Table 3.5). The Pearson correlation coefficients between the most severe sanction and the four estimated sanction probabilities are also highly significant. As expected, the coefficient for the 'No sanction'-group is negative, and the other coefficients are positive. All of these correlations are rather weak.

Table 3.5 A comparison of the qualitative and quantitative risk classifications using Pearson correlation coefficients (n=1419)

	Most severe sanction (2009)	CB risk classification (based on 2008 data)	Number of controls (2009)
Control body (CB) risk classification (based on 2008 data)	0.2189*	1	
Total number of controls in 2009	0.1773*	0.2320*	1
Estimated probability of 'No sanction' (based on 2008 data)	-0.2278*	-0.2844*	-0.1315*
Estimated probability of 'Slight sanction' (based on 2008 data)	0.2208*	0.2693*	0.1321*
Estimated probability of 'Critical sanction' (based on 2008 data)	0.1957*	0.2466*	0.1052*
Estimated probability of 'Severe or extreme sanction' (based on 2008 data)	0.1014*	0.1492*	0.0467[a]

Notes: * Significant at the 0.001 level; [a] p-value of 0.0789.

The method applied does not enable an evaluation regarding which of the two risk approaches is more accurate, but the method does provide support for both approaches. In general, the effect of a risk classification system is not easy to evaluate: operations that are classified as risky are more often controlled and perhaps even controlled more rigorously. Namely, the data that we analysed could already have been influenced by the risk perceptions and evaluations of the control body and inspectors. The degree to which this influence might be relevant is difficult to assess. This problem is illustrated by the correlation between the number of controls and the CB's risk classification.

The remarkable decline in sanctioned farmers, as illustrated in Table 3.2, coincided with the coming into force of the revised European organic regulation in 2009. One might be tempted to explain the decreased sanction frequency by referring to the revised

[7] We could not perform similar analyses for 2008, as we did not have a risk classification from the CB for this year.

regulation. However, according to expert evaluations of the revision process, the revised regulation does not sufficiently explain this development. Few changes in production rules were observed (Plakolm, 2009), and the control measures were expected to remain constant in Germany (Neuendorff, 2009). The revision and the subsequent adaptation processes of the stakeholders may have induced the inspectors and control bodies to act more generously in the corresponding year. An alternative explanation might be that some unobserved factors (e.g., a changed population of inspectors) are responsible for the difference.

3.6 Conclusion

The organic certification sector is legally obligated to implement a risk-based control approach. Thus far, both simple and elaborate qualitative methods that may involve the ‘gut instincts’ of inspectors have been applied. Although the discussion of risk-based controls has persisted for years and considerable expectations are connected to this approach, little systematic progress with regard to control effectiveness and efficiency has been achieved.

Against this background, our contribution is based on a categorical analysis of data from an important German organic control body and analyses risk quantitatively in terms of sanction probabilities. The estimations provide reliable results, especially with regard to general farm characteristics, such as organic control experience, farmed area, and the existence of conversion areas for organic farming. However, the analysis of farm production characteristics (i.e., specific livestock or crop categories) does not yield clear results.

The data that were used in the ordinal logistic models are based on farm and control data that are similar to those available from all or most European control bodies. Proper data collection and data management with risk-based analysis objectives are prerequisites for sound quantitative analyses. The inclusion of additional variables that have not yet been collected by control bodies could increase the utility of a quantitative risk-based approach. Such data could include information pertaining to the financial situation of a farm and personal data with respect to a farmer (age, education, and organic experience). To better capture seasonal effects, researchers could employ market data (to capture price changes) and production-relevant climate data (to capture difficult production situations) to further enhance quantitative risk modelling. Some of these types of data are currently implicitly evaluated by inspectors who visit farms and communicate with farmers. Capturing these impressions is likely to represent an important advantage of qualitative risk assessment over quantitative risk assessment. The evaluation of these soft factors and the systematic incorporation of relevant proxies into the control databases could offer further benefits for risk-based controls.

An ordinal logistic regression analysis allows for the modelling of different sanction categories. However, this method relies on the parallel regression assumption that is often violated in real-world data sets. Panel modelling could alternatively be applied in situations in which more extended time series data are available. This alternative would enable researchers to gain a clearer understanding of the effects of organic experience and to test for seasonal production and market effects. Count data modelling could also be an alternative method, although this type of modelling would need to rely on significantly larger populations because severe sanctions rarely occur.

The applicability of a quantitative risk analysis requires both technical and methodological skills that are not usually available to a control body. Technical services are regularly provided by external professional service providers. The methodological skills that are applied in this analysis do not represent the core business of control bodies. However, in the long term, the integration of more developed methods into the database systems of control bodies may be feasible. Until this integration will be completed, we suggest strengthening the qualitative risk-based approach by further elaborating the quantitative risk analysis method and integrating this approach into control governance. The suggested approach is a promising means of deriving benefit from the potential effectiveness and efficiency gains that risk-based control approaches imply.

3.7 References

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4 Econometric analysis of non-compliance with organic farming standards in Switzerland[1]

Authors: Christian Lippert, Alexander Zorn, Stephan Dabbert

Abstract Applying the *economics of crime theory*, we model the decision of an opportunistic and/or careless organic farmer and derive hypotheses to explain non-compliance. Some of the hypotheses are tested against empirical data on farm characteristics and imposed sanctions as proxy variables for non-compliance in the years 2007 through 2009 for organic farms certified by Bio Suisse. *Random effects logit models* show that processing activities and livestock diversity significantly increase a farm's sanction probability. Past non-compliances also indicate a higher present sanction probability. Finally, we discuss some methodological issues and suggest a way to organise risk-based inspections more effectively.

Keywords: Organic farming, non-compliance, economics of crime, effective control system, random effects logit model

JEL classification: Q12, K42, C25

Acknowledgement: This article was generated 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. The article 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. Special thanks for highly valuable comments on an earlier version of this paper go to Danilo Gambelli, Francesco Solfanelli and Raffaele Zanoli. Remaining errors and mistakes are ours.

[1] This chapter consists of an unpublished manuscript that is to be submitted to a scientific journal.

4.1 Introduction

Reliable and cost-effective certification is an important matter for consumers (cf., e.g., WARD et al., 2004) and producers (cf., e.g., SCHULZE et al., 2008) of organic produce, which is characterised by (credence) process qualities that are difficult to monitor (cf. JAHN et al., 2005). Hence, opportunistic producers may try to cheat by selling cheap food that is produced without adhering to the organic standard, at high organic market prices. Therefore, "repeat-purchase relationships and third-party monitoring are required for high-quality credence goods to be available" (MCCLUSKEY, 2000). The objective of this paper is to theoretically and empirically analyse non-compliance behaviour of organic farmers so as to elaborate starting points for a more effective risk-based inspection and certification of organic farms.

The theory developed herein is based on the *economics of crime approach*[2], the principles of which have been developed by BECKER (1974; 1976) and STIGLER (1970). For given standards, an economic model explaining organic farmers' non-compliance should reproduce the following relationships: we suppose that the incidence of non-compliance with organic standards is affected, on the one hand, by farmers' compliance costs. On the other hand, it is thought to be influenced by inspection frequencies and the closely related probability of detecting non-compliance as well as by deterring fines and further (indirect) sanctions resulting from marketing restrictions in the case of detected non-compliance. Thus, similar to other cases of offences (cf. EHRLICH, 1974; EIDE et al., 1994; ANTONY and ENTORF, 2002), in our theoretical model, we assume a negative relationship between the incidence of non-compliance and perceived inspection frequency.

In chapter 4.2, a theoretical model for the explanation of organic farmers' non-compliance is presented. From this model, hypotheses on the effects of non-compliance determining factors are derived. Chapter 4.3 contains a statistical analysis of some of these hypotheses. For this purpose, we rely upon 2007 to 2009 panel data on Swiss organic farmers' characteristics and their compliance with *Bio Suisse* standards. Chapter 4.4 offers a discussion of the results along with our main conclusions.

2 HERZFELD and JONGENEEL (2008, p.3ff.) provide a brief overview on the *economics of crime* approach with special regard to compliance in agriculture. For an application to food safety performance standards see LIPPERT (2002).

4.2 Theoretical model

We assume that part of the organic farmers inspected by a control body will behave opportunistically. They will make only insufficient efforts to comply with a certain organic standard or even deliberately cheat in case the expected sanctions, which they have to fear when detected, are low when compared to compliance costs. As farmers' individual risk attitudes are rather difficult to observe for a first approach, we assume risk-neutrality so that an opportunistic farmer's change in expected profit is proportionate to the resulting expected utility change. However, the statistical analysis in chapter 4.3 indirectly deals with farmers' different attitudes towards risk as part of the unobserved heterogeneity. Consequently, similar to the approach by ALMER and GOESCHL (2008, p.6f.), an opportunistic farmer's compliance decision is assumed to be described by the following condition: If

$$H[B|NC_{it}=1]=C_t\left(s_i, fs_i, ft_i, fe_i, fl_i\right)-P_d\left(s_i, fs_i, ft_i, IF_{t-1}, IR_{t-1}\right)P_s\left(SF_{t-1}\right)\left(F+L\left(s_i, fs_i, ft_i, d\left(fl_i\right)\right)\right)+\varepsilon_{it}>0 \quad (4.1)$$

then NC_{it} = 1, NC_{it} = 0 otherwise, with

H[.] = expectation of .
t = time period (year)
i = farm number (i = 1, …, n)
$B|.$ = net benefit given .
NC = non-compliance (NC_{it} = 1 if farmer *i* does not comply at time *t*, NC_{it} = 0 otherwise)
C = compliance cost saved when infringing upon the standard; these cost depend on
  s = site (location of the farm)
  fs = farm size (e.g., measured in UAA of the farm)
  ft = farm type (e.g., assessed by means of dummy variables for certain livestock activities or in case certain crops are cultivated)
  fe = farmer's experience (e.g., measured in years of organic farming practice)
  fl = farmer's liquidity
P_d = (subjective) probability of being detected in case of non-compliance depending on *s*, *fs*, *ft* as well as on
  IF = (perceived) inspection frequency and
  IR = (perceived) inspection rigour (e.g., determined by inspection duration and accuracy observed during former inspection visits)
P_s = probability of getting a sanction when being detected which depends on
  SF = (perceived) sanction frequency in case of detected non-compliance
F = fine related to the sanction (assumed to be given and constant over time)

L = present value of future profits lost due to sanction related marketing restrictions and reputation losses which depend on s, fs, ft as well as on
d = discount rate (also influenced by the farmer's liquidity fl)
ε_{it} = error term reflecting further individually different cost and/or benefit determining factors, such as a farmer-specific risk premium, as well as a random error.

It should be noted that costs, C_i, do not only contain (opportunity) costs directly resulting from compliance with the respective organic standards but also related information and transaction costs. These costs are individually influenced by every farmer i's education along with her cognitive capabilities. Presented this way, a careless non-complying farmer who, at first glance, does not act opportunistically as she is not cheating consciously may, nevertheless, be perceived as behaving according to inequality (4.1). That is, being inaccurate, she implicitly evaluates cost, C_i, which, in practice, also includes all costs for obtaining information needed to be accurate, as exceeding the monetary value of expected sanctions.

In addition to a farmer-specific risk premium (reducing ε_{it}), the term ε_{it} may also reflect an individually different monetary equivalent of a "warm glow" due to the positive feelings when complying with organic farming standards. For many well-informed farmers, this equivalent may be so important that they will always comply regardless of how costly it will be. Organic farmers consist of two subgroups. For non-opportunistic actors NC_{it} is always zero, whereas for the other (the opportunistic) farmers, compliance behaviour is determined by the variables contained in inequality (4.1).

In the case where a control body has already assigned the monitored farms to different risk classes subject to different inspection frequencies, the perceived inspection frequency, IF_{t-1}, is a function of those variables that determined the corresponding classification (i.e., in inequality (4.1): $IF_{t-1} = IF_{t-1}(fs_i; ft_i; .)$).

Let x_{ijt} be one factor among other factors that determines farmer i's benefit of non-compliance $B_t|NC_{it}$=1 with a given organic standard. Then, for well specified direct and indirect sanctions, F and L, it follows from inequality (4.1) that as long as

$$\frac{\partial B_t \left| NC_{it} = 1\right.}{\partial x_{ijt}} = \frac{\partial B_t}{\partial x_{ijt}} > 0 \tag{4.2}$$

an increase of the factor x_{ijt} entails

(i) a rising probability, $P(NC_{it} = 1)$, of farmer i infringing upon the considered standard and

(ii) a greater total number, NCF, of non-complying organic farmers as inequality (4.1) will be positive for more opportunistic actors.

Inequality (4.1) yields the following partial derivatives and corresponding hypotheses:

$$\frac{\partial B_t}{\partial P_d} = -P_s(.)\big(F + L(.)\big) < 0 \qquad => \tag{4.2a}$$

Hypothesis: $P(NC_{it} = 1)$ and the number of non-complying farmers, NCF, decreases with the probability of being detected in case of non-compliance;

$$\frac{\partial B_t}{\partial P_s} = -P_d(.)\big(F + L(.)\big) < 0 \qquad => \tag{4.2b}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with the probability of receiving a sanction when detected;

$$\frac{\partial B_t}{\partial IF_{t-1}} = -P_s(.)\big(F + L(.)\big)\frac{\partial P_d(.)}{\partial IF_{t-1}} < 0 \quad \left(because \quad \frac{\partial P_d(.)}{\partial IF_{t-1}} > 0\right) \quad => \tag{4.2c}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with a higher (perceived) inspection frequency at time t-1;

$$\frac{\partial B_t}{\partial IR_{t-1}} = -P_s(.)\big(F + L(.)\big)\frac{\partial P_d(.)}{\partial IR_{t-1}} < 0 \quad \left(because \quad \frac{\partial P_d(.)}{\partial IR_{t-1}} > 0\right) \quad => \tag{4.2d}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with inspection rigour at time t-1;

$$\frac{\partial B_t}{\partial SF_{t-1}} = -P_d(.)\big(F + L(.)\big)\frac{\partial P_s(.)}{\partial SF_{t-1}} < 0 \quad \left(because \quad \frac{\partial P_s(.)}{\partial SF_{t-1}} > 0\right) \quad => \tag{4.2e}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with (perceived) sanction frequency when detected at time t-1;

$$\frac{\partial B_t}{\partial fe} = \frac{\partial C_t(.)}{\partial fe} < 0 \qquad => \tag{4.2f}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with a farmer's experience because it is assumed that the longer a person has farmed organically, the easier it will be for her to comply with the standard;

$$\frac{\partial B_t}{\partial fl} = \frac{\partial C_t(.)}{\partial fl} - P_d(.)P_s(.)\frac{\partial L(.)}{\partial d(fl)}\frac{\partial d}{\partial fl} < 0 \qquad => \tag{4.2g}$$

Hypothesis: $P(NC_{it} = 1)$ and NCF decrease with a farmer's liquidity because it is assumed that it is less costly to bear present costs or to renounce to present income from fraud when having more liquid assets today (i.e., $\partial C_t(.)/\partial fl$ < 0) and because $\partial L(.)/\partial d(fl)$ and $\partial d/\partial fl$ are unambiguously negative;

$$\frac{\partial B_t}{\partial fs} = \frac{\partial C_t(.)}{\partial fs} - P_s(.)\big(F + L(.)\big)\frac{\partial P_d}{\partial fs} - P_d(.)P_s(.)\frac{\partial L(.)}{\partial fs} \qquad (4.2h)$$

Hypothesis: The direction of the effect of an increasing farm size on $P(NC_{it} = 1)$ and *NCF* is not clear. Whereas the second and third addend of (2h) are both supposed to be negative ($\partial P_d/\partial fs > 0$ because the bigger the farm the more opportunities to detect non-compliance and $\partial L(.)/\partial fs > 0$ because the bigger the farm the more harmful the future marketing restrictions will be) it is unclear how $\partial C_t(.)/\partial fs$ will behave. It could be negative due to economies of scale, but it could also be positive because, with increasing farm size, there will be more costly aspects to observe and increased opportunities to make mistakes.

Hypothesis: Site *s* and farm type *ft* are categorical variables that may influence $B_t | NC_{it} = 1$ (4.2i)

As assumed in inequality (4.1), the detection probability P_d is affected by some of the variables explaining non-compliance; thus, a general problem arises when trying to estimate the discussed effects by means of discrete choice models (see chapter 4.3). This problem results from the fact that *observed* non-compliance, which is used to estimate the probability of non-compliance, is not the same as *real* non-compliance. This may be illustrated for constant detection probabilities $P_d = P_{d(t-1)} = P_{d(t)}$ using farm size, *fs*, as an example. Neglecting $\partial L(.)/\partial fs$ and assuming $\partial C_t(.)/\partial fs = 0$ and $\partial P_d/\partial fs > 0$, it follows from (4.2h) that an increase in farm size leads to a reduced number, *NCF*, of non-complying farmers. However, what would be observed is the *reported* number, *RNCF*, of non-complying farmers

$$RNCF\big(P_d(fs,.),.\big) \quad = \quad NCF\big(P_d(fs,.),.\big)\cdot P_d(fs,.). \qquad (4.3)$$

Whereas in the example, the marginal effect of farm size on *real* non-compliance is

$$\frac{\partial NCF\big(P_d(fs,.),.\big)}{\partial fs} \quad = \quad \frac{\partial NCF}{\partial P_d}\frac{\partial P_d}{\partial fs} \quad < \quad 0, \qquad (4.4)$$

the observed marginal effect on *reported* non-compliance can be positive because in equation

$$\frac{\partial RNCF\left(P_d\left(fs,.\right),.\right)}{\partial fs} = P_d\left(fs,.\right)\frac{\partial NCF}{\partial P_d}\frac{\partial P_d}{\partial fs}+NCF\left(P_d\left(fs,.\right),.\right)\frac{\partial P_d}{\partial fs} \tag{4.5}$$

the second addend on the right-hand side is greater than zero. In other words, the reduction of equilibrium non-compliances due to the deterring effect of a higher detection probability may be overcompensated by the increased number of *detected and reported* non-compliances. In this case, the conclusion that bigger farm size leads to more (*true*) non-compliance would be wrong. Note that the discussed problem is relevant for all non-compliance explaining variables that affect not only *C(.)* and *L(.)* in equation (4.1) but also probability P_d.

4.3 Statistical models to explain organic farmers' non-compliance in Switzerland

4.3.1 Data

The following empirical analysis is based on data from the years 2007 through 2009 for inspections, sanctions and farm characteristics provided by an important Swiss organic certification body. *Table 4.1* contains summary statistics of those available variables that are used for hypothesis testing in this study. For each of the years, 2007, 2008 and 2009, the number of clients from the considered certification body that showed at least some kind of organic farming activity was 4661, 4508 and 4387, respectively.

In total, *Table 4.1* covers data from 4831 farms, out of which 4215 farms were certified every year within the three year period. 215 farms were certified only in 2007 and 2008 and 70 farms were listed for 2008 and 2009. Another 10 farms were lacking data for 2008. The number of farms that were certified for only one of the three years, according to the dataset was 221 (2007), 8 (2008) and 92 (2009).

On average, every farm was inspected approximately 1.06 times in 2007 (see *Table 4.1*). This value includes 1.01 regular annual inspections, 0.0006 follow-up visits in case of previous non-compliances and 0.046 unannounced controls. The corresponding figures were similar for the years 2008 and 2009. However, the number of unannounced visits increased slightly to 0.057 in 2009.

Table 4.1 Summary statistics for selected variables of Swiss organic farms certified by an important certification body

Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Year	2007 (n = 4661)		2008 (n = 4508)		2009 (n = 4387)	
Total number of controls of a farm	1.05793	0.253033	1.06477	0.252384	1.06633	0.255222
Number of annual inspections imposed on a farm	1.01094	0.129742	1.01375	0.118368	1.00935	0.100859
Number of follow-up inspections imposed on a farm	0.00064	0.025365	0.00044	0.021061	0.00023	0.015098
Number of unannounced inspections imposed on a farm	0.04634	0.211265	0.05058	0.222173	0.05676	0.233369
Number of slight and moderate sanctions imposed on a farm	0.01588	0.126716	0.01309	0.117503	0.01892	0.147505
Number of severe and extreme sanctions imposed on a farm	0.04291	0.215005	0.03283	0.181909	0.02713	0.166625
Organic control experience in 10 years	1.15856	0.664391	1.24854	0.671525	1.32947	0.680487
Farm's agricultural area (UAA) in square kilometres (km^2)	0.19504	0.181874	0.19252	0.148054	0.19901	0.168838
Farm is subjected to certification apart from Bio Suisse (yes=1)	0.95838	0.199745	0.96251	0.189978	0.97812	0.146318
Farm is also a processor (yes=1)	0.43553	0.495879	0.45075	0.497624	0.40415	0.490783
Shannon index for aggregated crop acreage [a)]	0.59056	0.308485	0.59859	0.304789	0.60165	0.30671
Shannon index for livestock [b)]	0.25235	0.310877	0.25333	0.314338	0.25262	0.315606
Farm cultivates GMO risk crops (soya or maize; yes=1)	0.02961	0.169520	0.02374	0.152241	0.02325	0.150715
Farm with relevant cereals, incl. rice (yes=1) [c)]	0.14782	0.354962	0.14707	0.354217	0.14862	0.355755
Farm with relevant dried pulses (yes=1) [c)]	0.01395	0.117277	0.01553	0.123654	0.01482	0.120832
Farm with relevant root crops (yes=1) [c)]	0.07616	0.265289	0.07187	0.258305	0.07180	0.258191
Farm with relevant industrial crops (yes=1) [c)]	0.03862	0.192704	0.04304	0.202958	0.04582	0.209112
Farm with relev. fresh vegetables, melons, strawber. (yes=1) [c)]	0.03454	0.182636	0.03660	0.187802	0.03761	0.190276
Farm with relevant green fodder from arable land (yes=1) [c)]	0.71315	0.452339	0.71806	0.449996	0.71917	0.449456
Farm with relevant other arable land crops (yes=1) [c)]	0.08453	0.278213	0.08385	0.277195	0.08799	0.283309
Farm with relevant permanent grassland (yes=1) [c)]	0.72796	0.445061	0.73159	0.443182	0.73672	0.440462
Farm with relevant fruit and berries (yes=1) [c)]	0.05707	0.232000	0.05812	0.233994	0.05904	0.235723
Farm with relevant grapes (yes=1) [c)]	0.02274	0.149096	0.02241	0.148012	0.02302	0.149992
Farm with relevant unutilised land (yes=1) [c)]	0.27784	0.447981	0.29791	0.457393	0.30294	0.459582
Farm with relevant other crops (yes=1) [c)]	0.01695	0.129095	0.01752	0.131229	0.01869	0.135449
Farm with relevant bovine animals (yes=1) [c)]	0.58314	0.493093	0.58119	0.493419	0.58491	0.492794
Farm with relevant pigs (yes=1) [c)]	0.08539	0.279490	0.07742	0.267283	0.07431	0.262305
Farm with relevant sheep (yes=1) [c)]	0.21090	0.407991	0.20963	0.407088	0.20903	0.406660
Farm with relevant goats (yes=1) [c)]	0.13838	0.345338	0.14907	0.356195	0.15364	0.360640
Farm with relevant poultry (yes=1) [c)]	0.31109	0.46299	0.29592	0.456505	0.28949	0.453578
Farm with relevant equids (yes=1) [c)]	0.13388	0.340557	0.13798	0.344914	0.14064	0.347692
Farm with relevant rabbits (yes=1) [c)]	0.04570	0.208853	0.04281	0.202457	0.03830	0.191929
Farm with relevant bees (yes=1) [c)]	0.02274	0.149096	0.02662	0.160986	0.02120	0.144064

[a)] *Crop Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s land for activity *k* divided by overall farmland of farm *i* (k = 1, …, 16 at maximum; activities according to *Eurostat* level 1 categories: cereals, root crops, permanent grassland etc.). - [b)] *Livestock Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (k = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids etc.). - [c)] *relevant* means farm *i*'s area or livestock units exceed a threshold corresponding to the first quartile of all data entries for the corresponding attribute within the considered three-year period.

Source: own calculations based on data from a Swiss organic certification body, 2007-2009

In all three years, there were fewer slight and moderate sanctions (0.0159, on average, in 2007) than severe or extreme ones (0.0429 per farm-operator in 2007). However, the mean severe and extreme sanctions per farm declined between 2007 and 2009, whereas the slight and moderate sanctions increased when comparing the respective values for 2007 and 2009.

Table 4.1 also contains summary statistics for important potential explanatory variables. In 2007, the mean farm's experience with the organic certification body, which provided the data, was approximately 11.6 years. The maximum experience reported by one farm (approximately 78 years, not shown in the table) could be a mistake or the result of a misunderstanding in the way that, in this single case, the corresponding farm's experience in organic farming was given. Regarding the utilised agricultural area (UAA) in 2007, the smallest farm-operator cultivated 0.02 hectares, whereas the biggest farm consisted of a UAA of 450 hectares. Furthermore, in 2007 and 2008, 96% (98% in 2009) of the farms also participated in another certification scheme and between 40% and 45% reported a processing activity while up to 3% cultivated so-called *"GMO risk crops"* (i.e., soya or maize).

Table 4.1 also contains the summary statistics for some crop and livestock dummy variables. For instance, the 2007 dummy variable *farm with relevant bovine animals* has to be interpreted as follows: 58.3% of the farms kept cattle and were among the 75% biggest cattle raising farms certified by the considered certification body in Switzerland. The *Crop Shannon index* is a measure for cropping diversity which simultaneously captures the number of crop categories cultivated and the shares of the crops in overall acreage. Similarly, the *Livestock Shannon index* is a measure for livestock diversity which simultaneously captures the number of animal species kept and the shares of the species in overall livestock units.

4.3.2 Statistical models

The main objective of our statistical analysis is to explain the probability *P* of detecting non-compliance with *Bio Suisse* organic standards in a certain organic farm. As there are only very few cases with more than one reported sanction per sanction category and year, we do not consider count data (Poisson regression) models. Instead, binary choice models will be estimated. As we are initially dealing with panel data, we estimate *random effects logit models* (cf. CAMERON and TRIVEDI, 2010, p.625ff.; ALLISON, 2010, p.75f.). Fixed effects models, in this case, do not make sense because there is minimal variation in the explanatory variables within the individual farms (e.g., a farm raising cattle in 2007 will usually also keep cattle in 2008 and 2009). The latent-variable model underlying the following estimations is given by:

$$y_{it}^* \;=\; \alpha_i + \sum_{j=1}^{l} \beta_j x_{ijt} + \omega_{it} \;; \qquad y_{it} = \begin{cases} 1 \; if \;\; y_{it}^* > 0 \\ 0 \; if \;\; y_{it}^* \leq 0 \end{cases} \tag{4.6}$$

where y_{it} = 1 if at least one sanction of the considered sanction category was reported in year t, 0 otherwise. Models for the two different sanction categories in *Table 4.1* are estimated. In doing so, the dummy variable *sanction* is taken as a proxy variable for a certain kind of *reported non-compliance*. To the extent possible, the explanatory variables, x_{jt}, are chosen to test part of hypotheses (4.2a) through (4.2i) in chapter 4.2, while the influence of unavailable explanatory variables as well as of ε_{it} in inequality (4.1) is supposed to be captured by ω_{it}.

x_{1t} = *organic control experience* as the difference between year t and year of contract date divided by 10 as a proxy for the farmer's organic farming experience, *fe* (expected sign of β_1: negative, see hypothesis (4.2f))[3];

x_{2t} = *UAA in square kilometres* as a proxy for farm size, *fs* (expected sign of β_2: unclear, see (4.2h) and equation (4.5) in chapter 4.2);

x_{3t} = proxy variables for different farm types, *ft*, are obtained from available dummy variables (see *Table 4.1*; expected sign of β_3 is dependent on farm types and sites; for the dummy variables *farm is also a processor* and farm cultivates *GMO risk crops,* the expected sign is positive as we believe that these attributes make non-compliance more likely due to further sources of error; the two *Shannon indices* are expected to positively affect the sanction probability as well because an increase reflects a rising farm complexity);

x_{4t} = a dummy variable, which is one when a farm submits to at least one further *certification apart from Bio Suisse* (see *Table 4.1*; expected sign of β_4 is negative as additionally certified farmers are expected to be more committed to organic farming – leading to a lower ε_{it} in inequality (4.1) –, to be better informed about all relevant standards – leading to lower cost, C_i, in inequality (4.1) – and to suffer from higher losses, L_i, if not allowed to market their produce organically).

[3] The respective time spans are divided by ten to obtain a variable, the standard deviation of which has an order of magnitude similar to the standard deviations of the other explanatory variables. Otherwise, problems with the estimation procedure could occur (cf. LONG and FREESE, 2006, p.77f.).

The effectiveness of unannounced controls is tested by adding the variable *number of unannounced inspections imposed on a farm* to the list of explanatory variables retained in the restricted models.

Unfortunately, some of the hypotheses derived from the theoretical *economics of crime model* in chapter 4.2 cannot be tested as this would require a longer time series or further variables, such as testing the influence of liquidity assets, *fl* (see hypothesis (4.2g)), for which we did not have any proxy variable.

Because we are dealing with random effects models, we will not know the effects α_i of the individual farms, and it is impossible to predict the probabilities $P(y_{it} = 1|x_{ijt}; \beta_j; \alpha_i)$; however, the sign of coefficient β_j corresponds to the sign of the respective marginal effect $\partial P/\partial x_{ijt}$ and the latter is also proportionate to β_j (cf. CAMERON and TRIVEDI, 2010, p.625f.).

For the years 2008 and 2009, we also estimate cross-sectional logit-models with time-lagged sanction variables as additional explanatory variables to examine whether the occurrence of non-compliance in the past increases the probability of present non-compliance. A farm's past non-compliance could signal higher compliance cost, lower losses, L_i, risk friendly behaviour and/or lower commitment to organic farming.

4.3.3 Results

4.3.3.1 Slight and moderate sanctions

First, we explain the dummy variable *slight and moderate sanction* via a backwards stepwise procedure with the possible explanatory variables in *Table 4.1* (except variables on number of controls/inspections and number of sanctions). The restricted model, which contains only significant coefficients, is displayed in *Table 4.2*. Notice that a population-averaged model with panel-robust standard errors and assumed time-lag independent (exchangeable) error correlation (cf. CAMERON and TRIVEDI, 2010, p.624f.) results in the same significant variables and directions of the corresponding effects.

Some of the explanatory variables considered in this analysis are significantly correlated, resulting in the occurrence of a multi-collinearity problem. The Shannon crop index and the Shannon livestock index are strongly correlated with some of the crop and livestock dummies used. The same holds for the farms' UAA, the control experience and, to a lesser extent, the processor dummy. Moreover, for a first approach, we use the available crop and livestock dummies shown in *Table 4.1* as rough proxies for different farm types. However, we cannot provide a reasonable hypothesis for all significant dummies in *Table 4.2*. For instance, we have no clear idea why farms with other crops, farms with unutilised land or farms with equids demonstrate a higher probability of non-compliance.

Table 4.2 Random-effects logistic regression for slight and moderate sanctions (results of a backwards stepwise procedure with available potential explanatory variables)

Slight and moderate sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm is subjected to certification apart from Bio Suisse (yes=1)	-0.73187	0.324192	-2.26	0.024	-1.367277	-0.096469
Farm is also a processor (yes=1)	0.40622	0.158892	2.56	0.011	0.094801	0.717648
Shannon index for aggregated crop acreage [a)]	-0.74380	0.351193	-2.12	0.034	-1.432125	-0.055476
Shannon index for livestock [b)]	0.77509	0.246653	3.14	0.002	0.291658	1.258517
Farm with relevant cereals, incl. rice (yes=1) [c)]	0.74241	0.232685	3.19	0.001	0.286359	1.198468
Farm with relevant other arable land crops (yes=1) [c)]	0.63973	0.267723	2.39	0.017	0.115004	1.164459
Farm with relevant permanent grassland (yes=1) [c)]	-0.37083	0.168274	-2.20	0.028	-0.700643	-0.041021
Farm with relevant unutilised land (yes=1) [c)]	0.44884	0.162877	2.76	0.006	0.129603	0.768068
Farm with relevant equids (yes=1) [c)]	0.41389	0.209210	1.98	0.048	0.003848	0.823937
Constant	-4.32055	0.408928	-10.57	0.000	-5.122029	-3.519061
/lnsig2u	0.37515	0.329971			-0.271578	1.021886
sigma_u	1.20632	0.199026			0.873027	1.666863
rho	0.30668	0.070161			0.188097	0.457860

[a)] *Crop Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s land for activity *k* divided by overall farmland of farm *i* (*k* = 1, …, 16 at maximum; activities according to *Eurostat* level 1 categories: cereals, root crops, permanent grassland, etc.). - [b)] *Livestock Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (*k* = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids etc.). - [c)] *relevant* means farm *i*'s area or livestock units exceed a threshold corresponding to the first quartile of all data entries for the corresponding attribute within the considered three-year period.
Number of observations = 13556; number of groups = 4831. - Random effects u_i ~ Gaussian; observations per group: minimum = 1, average = 2.8, maximum = 3. - Wald $chi^2(9)$ = 73.25; Log likelihood = -1026.4081; Prob. > chi^2 = 0.0000. - Likelihood-ratio test of rho = 0: $chibar^2(01)$ = 11.42, Prob. >= $chibar^2$ = 0.000.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

For both reasons, that is, multi-collinearity and lack of hypotheses behind some dummy variables, we perform a second backwards stepwise procedure with a reduced set of explanatory variables excluding all crop and livestock dummies except the GMO risk crops and the permanent grassland dummy, both of which are justified by reasonable hypotheses. We expect a higher probability of non-compliance in the case of GMO risk crops and a lower probability for grassland farms that are expected to benefit less from forbidden pesticides. The corresponding results are displayed in *Table 4.3*.

Table 4.3 Random-effects logistic regression for slight and moderate sanctions (results of a backwards stepwise procedure with selected potential explanatory variables)

Slight and moderate sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm's agricultural area (UAA) in square kilometres (km^2)	0.69471	0.336718	2.06	0.039	0.034757	1.354665
Farm is subjected to certification apart from Bio Suisse (yes=1)	-0.72996	0.324726	-2.25	0.025	-1.366407	-0.093505
Farm is also a processor (yes=1)	0.40025	0.155946	2.57	0.010	0.094605	0.705900
Shannon index for livestock [a)]	1.07210	0.216466	4.95	0.000	0.647834	1.496365
Farm cultivates GMO risk crops (soya or maize; yes=1)	0.73907	0.355261	2.08	0.037	0.042773	1.435372
Farm with relevant permanent grassland (yes=1) [b)]	-0.52976	0.171982	-3.08	0.002	-0.866842	-0.192684
Constant	-4.52911	0.393108	-11.52	0.000	-5.299587	-3.758634
/lnsig2u	0.45206	0.310617			-0.156733	1.060862
sigma_u	1.25362	0.194697			0.924626	1.699665
rho	0.32327	0.067953			0.206266	0.467549

[a)] *Livestock Shannon Index* = – ∑ $share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (*k* = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids, etc.). - [b)] *relevant* means farm *i*'s grassland area exceeds a threshold corresponding to the first quartile of all data entries for grassland area within the considered three-year period.
Number of observations = 13556; number of groups = 4831. - Random effects u_i ~ Gaussian; observations per group: minimum = 1, average = 2.8, maximum = 3. - Wald $chi^2(6)$ = 53.41; Log likelihood = -1036.8699; Prob. > chi^2 = 0.0000. - Likelihood-ratio test of rho = 0: $chibar^2(01)$ = 13.12, Prob. >= $chibar^2$ = 0.000.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

Using a farm's agricultural area as a proxy variable of farm size, we expect an effect, but due to theoretical considerations, we did not postulate a specific direction (see hypothesis (4.2h) in section 4.2). All other significant coefficients in *Table 4.3* have the expected sign. Accordingly, a farm submitting to further certification bodies should be better informed and more committed to organic farming, thus making fewer mistakes, whereas farms with processing activities, farms with greater livestock diversity and/or farms that cultivate GMO risk crops are more likely to infringe upon one or more of the rules included in the organic standard.

However, the fact that only a few farms are not subjected to further *certification apart from Bio Suisse* (see *Table 4.1*) is somehow problematical because the significant effect in *Table 4.3* is based on merely 12 sanctioned farms without further certification (see *Table 4.5*). Moreover, using the *number* of further certification schemes rather than the corresponding *0/1-dummy* in *Table 4.3* results in a significant effect with the opposite sign (see *Table 4.4*), which is difficult to interpret. Nevertheless, the other effects remain stable even though the processor dummy is now only significant at the 10% level; therefore, it is not included in *Table 4.4*. The distribution of cases with different numbers of additional certification schemes apart from *Bio Suisse* among farms with and without slight and moderate sanctions is displayed in *Table 4.5*.

Table 4.4 Random-effects logistic regression for slight and moderate sanctions (results of a backwards stepwise procedure with selected potential explanatory variables)

Slight and moderate sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm's agricultural area (UAA) in square kilometres (km^2)	0.62457	0.321456	1.94	0.052	-0.005472	1.254611
Number of certification schemes apart from Bio Suisse	1.37872	0.170205	8.10	0.000	1.045128	1.712319
Shannon index for livestock [a)]	0.96250	0.206564	4.66	0.000	0.557639	1.367354
Farm cultivates GMO risk crops (soya or maize; yes=1)	0.65914	0.342168	1.93	0.054	-0.011492	1.329780
Farm with relevant permanent grassland (yes=1) [b)]	-0.46433	0.166556	-2.79	0.005	-0.790772	-0.137887
Constant	-6.24275	0.324385	-19.24	0.000	-6.878535	-5.606970
/lnsig2u	-0.10508	0.470953			-1.028136	0.817968
sigma_u	0.94881	0.223424			0.598058	1.505288
rho	0.21485	0.079445			0.098059	0.407845

[a)] *Livestock Shannon Index* = – ∑ $share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (*k* = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids, etc.). - [b)] *relevant* means farm *i*'s grassland area exceeds a threshold corresponding to the first quartile of all data entries for grassland area within the considered three-year period.
Number of observations = 13556; number of groups = 4831. - Random effects u_i ~ Gaussian; observations per group: minimum = 1, average = 2.8, maximum = 3. - Wald $chi^2(5)$ = 110.76; Log likelihood = -1015.2241; Prob. > chi^2 = 0.0000. - Likelihood-ratio test of rho = 0: $chibar^2(01)$ = 5.30, Prob. >= $chibar^2$ = 0.011.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

Table 4.5 Farms with different numbers of additional certification schemes apart from Bio Suisse among farms with and without slight and moderate sanctions [a)]

	Number of certification schemes apart from Bio Suisse				
Slight and/or moderate sanction imposed on a farm	0	1	2	3	Total
Farms with no sanction (0)	447	12,233	643	26	13,349
Farms with at least one sanction (1)	12	135	60	0	207
Total	459	12,368	703	26	13,556

[a)] Every farm is considered as one case in every year it was in the sample; therefore, in 2007, a farm can be assigned a 0, whereas the same farm is counted among cases with 1 in 2008.

Source: own calculations based on data from a Swiss organic certification body, 2007-2009

Adding a dummy variable for *unannounced inspections* to the variables displayed in *Tables 4.3* and *4.4*, respectively, and estimating two new random effects logit models yield, in both cases, a significant positive effect of unannounced controls (p=0.1%) on the occurrence of a slight and/or moderate sanction without relevant changes of the other coefficients. Hence, unannounced inspections seem to be effective (i.e., $\partial P_d / \partial IF > 0$). Notice that there are no strong correlations between any of the potential explanatory variables shown in *Table 4.1* and unannounced inspections. For this dummy variable, the highest point-biserial correlation is found for agricultural area (r=0.036), and the corresponding Pearson correlation coefficients are all below 0.04 even though 10 out of these 27 correlation coefficients are significant because of the high number of observations.

For the years 2008 and 2009, two cross-sectional logit-models with time-lagged sanction variables as additional explanatory variables yield significant positive coefficients of the dummy variable *slight and/or moderate sanctions in the previous year* (backwards stepwise procedure with the initial set of variables used when estimating the model in *Table 4.3*, p=5.4% for 2008 and p=0.1% for 2009). However, as there are only 3 (5) cases with both a sanction in 2008 (2009) and one in the year prior, this result is obviously based on very few influential cases. Here, again, the problem is that the overall share of farms with slight and/or moderate sanctions is relatively small (see *Table 4.1*).

4.3.3.2 Severe and extreme sanctions

We explain the dummy variable *severe and extreme sanction* again by a backwards stepwise procedure starting with the same set of variables as for the case of slight and moderate sanctions. The final retained significant coefficients along with corresponding test statistics and further information are shown in *Table 4.6*. Notice that the variable, *farm with relevant root crops,* is not significant at the 10% percent level in the unrestricted model (then p=17.2%).

For the same reasons as those given in the previous section, we do a second backwards stepwise procedure with the same reduced set of explanatory variables as the one used for slight and/or moderate sanctions. The resulting model is shown in *Table 4.7*. Again, we obtain the expected (in this case, highly significant) negative effect of being certified apart from *Bio Suisse* on the sanction probability. In this case, however, the sign of the effect does not change when replacing the dummy variable for further certification by the number of further certification schemes.

Table 4.6 Random-effects logistic regression for severe and extreme sanctions (results of a backwards stepwise procedure with available potential explanatory variables)

Severe and extreme sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm is subjected to certification apart from Bio Suisse (yes=1)	-0.91967	0.225288	-4.08	0.000	-1.361225	-0.478114
Farm is also a processor (yes=1)	0.25291	0.116898	2.16	0.031	0.023790	0.482023
Shannon index for livestock [b)]	0.46257	0.212785	2.17	0.030	0.045522	0.879623
Farm with relevant root crops (yes=1) [c)]	-0.50377	0.247597	-2.03	0.042	-0.989048	-0.018486
Farm with relevant bovine animals (yes=1) [c)]	0.49332	0.124611	3.96	0.000	0.249091	0.737556
Farm with relevant sheep (yes=1) [c)]	-0.39542	0.16539	-2.39	0.017	-0.719575	-0.071258
Farm with relevant goats (yes=1) [c)]	0.36557	0.159678	2.29	0.022	0.052611	0.678538
Farm with relevant bees (yes=1) [c)]	0.81177	0.287771	2.82	0.005	0.247747	1.375788
Year 2008	-0.29805	0.119975	-2.48	0.013	-0.533192	-0.062899
Year 2009	-0.47607	0.127602	-3.73	0.000	-0.726164	-0.225973
Constant	-3.65556	0.275163	-13.29	0.000	-4.194867	-3.116249
/lnsig2u	0.69611	0.166326			0.370121	1.022108
sigma_u	1.41631	0.117785			1.203291	1.667048
rho	0.37878	0.039138			0.3056095	0.4579151

[b)] *Livestock Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (k = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids, etc.). - [c)] *relevant* means farm *i*'s area or livestock units exceed a threshold corresponding to the first quartile of all data entries for the corresponding attribute within the considered three-year period.
Number of observations = 13556; number of groups = 4831. - Random effects u_i ~ Gaussian; observations per group: minimum = 1, average = 2.8, maximum = 3. - Wald $chi^2(10)$ = 81.92; Log likelihood = -1900.7385; Prob. > chi^2 = 0.0000. - Likelihood-ratio test of rho = 0: $chibar^2(01)$ = 68.40, Prob. >= $chibar^2$ = 0.000.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

Table 4.7 Random-effects logistic regression for severe and extreme sanctions (results of a backwards stepwise procedure with selected potential explanatory variables)

Severe and extreme sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm is subjected to certification apart from Bio Suisse (yes=1)	-0.90343	0.226249	-3.99	0.0000	-1.346869	-0.459990
Farm is also a processor (yes=1)	0.33037	0.118053	2.80	0.0050	0.098990	0.561748
Shannon index for aggregated crop acreage [a)]	-0.43621	0.200246	-2.18	0.0290	-0.828682	-0.043733
Shannon index for livestock [b)]	0.40196	0.180206	2.23	0.0260	0.048762	0.755157
Year 2008	-0.28816	0.120073	-2.40	0.0160	-0.523495	-0.052819
Year 2009	-0.46196	0.127631	-3.62	0.0000	-0.712110	-0.211807
Constant	-3.21566	0.274824	-11.70	0.0000	-3.754308	-2.677017
/lnsig2u	0.78068	0.159718			0.467635	1.093719
sigma_u	1.47748	0.117990			1.263414	1.727818
rho	0.39887	0.038296			0.326686	0.475737

[a)] *Crop Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s land for activity *k* divided by overall farmland of farm *i* (k = 1, …, 16 at maximum; activities according to *Eurostat* level 1 categories: cereals, root crops, permanent grassland, etc.). - [b)] *Livestock Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (k = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids, etc.).
Number of observations = 13556; number of groups = 4831. - Random effects u_i ~ Gaussian; observations per group: minimum = 1, average = 2.8, maximum = 3. - Wald $chi^2(6)$ = 46.92; Log likelihood = -1919.3791; Prob. > chi^2 = 0.0000. - Likelihood-ratio test of rho = 0: $chibar^2(01)$ = 76.89, Prob. >= $chibar^2$ = 0.000.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

Corresponding to our hypotheses, both processing activities and livestock diversity affect the sanction probability positively, similar to the results found for slight and moderate sanctions. Interestingly, an increase in crop diversity leads to a lower sanction probability. The significant negative effects of the years 2008 and 2009 reflect the decline of severe and extreme sanctions over time (see *Table 4.1*).

Regarding hypothesis (4.2f), in contrast to the models for slight and moderate sanctions, this time, we obtain the expected negative effect of certification experience. However, as this effect is not significant, the expected effect of the organic farming experience could not be confirmed.

Again, adding a dummy variable for *unannounced inspections* to the variables displayed in *Table 4.7* and estimating a new random effects logit model results in a positive effect of unannounced controls (p=8.5%).

Finally, we estimate two cross-sectional logit models with time-lagged sanction variables as additional explanatory variables. By means of backwards stepwise estimation procedures with the same reduced set of initial explanatory variables used when estimating the model represented in *Table 4.7*, we obtain the results displayed in *Tables 4.8* and *4.9*.

Table 4.8 Cross-sectional logistic regression for severe and extreme sanctions in 2008 (results of a backwards stepwise procedure with selected potential explanatory variables)

Severe and extreme sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm is subjected to certification apart from Bio Suisse (yes=1)	-1.26746	0.288494	-4.39	0.0000	-1.832893	-0.702019
Severe and extreme sanctions in 2007 (yes=1)	1.89529	0.226747	8.36	0.0000	1.450874	2.339707
Shannon index for livestock [b)]	0.47920	0.259406	1.85	0.0650	-0.029224	0.987631
Farm's agricultural area (UAA) in square kilometres (km^2)	1.00335	0.375150	2.67	0.0070	0.268067	1.738628
Constant	-2.73423	0.288397	-9.48	0.0000	-3.299481	-2.168986

[b)] *Livestock Shannon Index* = $-\sum share_k \cdot ln(share_k)$ with $share_k$ = farm *i*'s calculated livestock units for activity *k* divided by overall livestock units of farm *i* (*k* = 1, …, 7 at maximum; activities according to *Eurostat* level 1 categories: bovine animals, sheep, equids, etc.).
Number of observations = 4436; LR $chi^2(4)$ = 76.77; Prob. > chi^2 = 0.0000; Log likelihood = -596.8378; Pseudo R^2 = 0.0604.

Source: own estimations based on data from a Swiss organic certification body, 2007-2008

In both years, the incidence of a severe sanction in one or (for 2009) two previous years significantly increases the probability of being penalised in the considered year. In contrast, the lagged slight and moderate sanctions do not yield a significant effect.

Table 4.9 Cross-sectional logistic regression for severe and extreme sanctions in 2009 (results of a backwards stepwise procedure with selected potential explanatory variables)

Severe and extreme sanctions imposed on farm (yes=1)	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Farm is subjected to certification apart from Bio Suisse (yes=1)	-0.89902	0.478655	-1.88	0.0600	-1.837162	0.039131
Farm is also a processor (yes=1)	0.47348	0.195036	2.43	0.0150	0.091219	0.855745
Severe and extreme sanctions in 2008 (yes=1)	1.23142	0.336485	3.66	0.0000	0.571917	1.890913
Severe and extreme sanctions in 2007 (yes=1)	1.25934	0.295033	4.27	0.0000	0.681089	1.837597
Constant	-3.12995	0.471202	-6.64	0.0000	-4.053489	-2.206412

Number of observations = 4227; LR $chi^2(4)$ = 38.48; Prob. > chi^2 = 0.0000; Log likelihood = -494.2983; Pseudo R^2 = 0.0375.

Source: own estimations based on data from a Swiss organic certification body, 2007-2009

4.4 Discussion and conclusions

First, it should be noted that the apparent effectiveness of unannounced inspections could also be an effect of suspicion linked to information that an inspector received during her regular annual on-farm inspection visit or because of whistle-blowing or information from processors or traders.

Next, the random effects models are based on the general assumption that farm-specific effects, α_i, are independent of x_{ijt} (cf. ALLISON, 2010, p.76f.). If the random variable, α_i, captures farm heterogeneity due to differences in farmers' current liquidity, their risk attitudes, cognitive abilities or education (all unknown variables that may influence compliance behaviour), this assumption appears justified as there is no obvious reason why these characteristics should be correlated with one of the explanatory crop or livestock variables contained in *Tables 4.2* and *4.6*. However, α_i may be correlated with the variable *farm is subjected to* [further] *certification apart from Bio Suisse* because this dummy variable could somehow capture commitment to organic farming and, hence, accuracy and skills in observing organic standards. In this case, the random effects estimators would be biased.

As outlined in chapter 4.2, different farm types may be characterised by different sanction-related losses and compliance costs that lead to different compliance behaviours. Consequently, in the event of similar social damages resulting from non-compliance, inspections should be farm-type specific by opting for a higher unannounced inspection frequency for farm categories with an increased past non-compliance incidence.

In this context, two severe problems arise. First, the estimated effects of risk increasing farm attributes could be biased by attribute dependent inspection rigours and intensities reflecting inspectors' prejudices or intuitions (i.e., a kind of a "confirmation bias"[4]). Second, one needs to be aware that the data on non-compliance frequencies are right censored as true non-compliances are very likely to lie above the observed (reported) non-compliances. Inevitably, the "dark figures", that is, the number of unreported non-compliances, will remain unknown. As has been presented in chapter 4.2, in cases where the detection probability depends on farm characteristics, this problem can bias conclusions regarding farm-type or size dependent incidences of certain non-compliances.

The obtained significant effects must be placed in the context of this "dark figure" problem. Whether an observed higher probability of non-compliance for a certain farm type, *ft* (e.g., characterised by one of the dummy variables with positive coefficients in *Table 4.6*) is really due to the fact that the considered farm type is more prone to non-compliance or whether this effect is merely due to better detection possibilities is an open issue. Only if we assume the detection probability P_d, in equation (4.1) to be independent of the attribute *ft*, we have observed significant effects on the true probability of non-compliance.

For instance, in the case of the significant negative effect of the participation in other certification schemes (apart from organic farming according to the *Bio Suisse* standards) on the sanction probability, the assumption of a detection probability independent from this attribute may be justified as organic farms, which are only *Bio Suisse* certified, are not necessarily characterised by specific production activities. Thus, it makes sense to suppose that farms that are not certified under additional schemes are more frequently non-compliers, as suggested by the statistical analysis, because for such farms losses, *L*, in inequality (4.1) may be lower.[5] In contrast, the observed increased sanction probability of farms that are also processors may be mainly due to a higher detection probability in such farms.

Assuming a farm-type independent detection probability, a strategy directing inspections towards farm types with a higher past non-compliance incidence would mean to direct

4 However, as reported in section 4.3.3.1, in our case, there are only relatively small correlations between the dummy variable for unannounced inspections and the significant explanatory variables found. Thus, there is no strong evidence for such a confirmation bias.

5 However, in this context it should be noted once more that 96% of the certified farms (in 2009 even 98%) were participating in further schemes.

inspections towards farmers who are *truly* more likely to infringe upon organic standards. However, even though it is merely a farm-type dependent higher detection probability entailing an increased non-compliance incidence, such a strategy would still be useful for directly avoiding more social damages resulting from non-compliance by withdrawing more faulty produce – which could cause damages or harmful scandals – from the market.

As demonstrated by our statistical analyses, discrete choice models can be used to determine farm characteristics that increase the probability of non-compliance and/or the probability of detection. In practice, these models may be continuously re-estimated with the most recent data. A continuous update of corresponding discrete choice models for non-compliance incidences is all the more necessary as farmers' expectations on future detection probabilities and sanctions are likely to be built upon observed past inspection and sanction frequencies. Hence, at some point in the future, they may change their compliance behaviour after a change in these frequencies. If so, control bodies should again adapt their inspection strategies. In our case, the dynamic character of the system is further illustrated by the decline of severe and extreme sanctions over time (see *Tables 4.1* and *4.7*). This decline could be due to a changed inspection and sanction behaviour of the certification body (e.g., reduced inspection accuracy or rigour), but it could also be caused by an adaptation of farm operators who realised the strict controls during the previous years.

Furthermore, in practice, control bodies can deliberately vary spot check inspection frequencies so that effects of increases in unannounced inspections ($\partial NCF/\partial IF_{t\text{-}1}$) can be approximated for different groups of organic farmers. However, such a statistical analysis would need huge time series data.

Finally, it should be emphasised that the relatively low Pseudo R^2 measures we obtain for the restricted models of our cross-sectional analyses indicate that important non-compliance risk affecting variables are still lacking in the Swiss dataset used. According to our theoretical analysis, such variables could include information about farms' site conditions as well as farmers' liquidity situation or attitudes towards risk. Additionally, further individual characteristics such as education and skills may play a role. In our statistical analysis, such farm-individual attributes may be captured by the significant effects of past non-compliances. However, if such personal attributes were available, again it could easily be that estimated effects are biased due to attribute dependent detection probabilities. For instance, if non-complying farmers with a higher level of education are smarter, it is likely that they will be caught less frequently than non-complying colleagues with a lower level of education.

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5 A heuristic model for optimizing the enforcement of organic farming standards[1]

Authors: Christian Lippert, Alexander Zorn, Stephan Dabbert

Abstract: This article theoretically analyzes strategies for the optimum enforcement of organic farming standards. Relying on *economics of crime theory*, the implicit decision calculus of opportunistic and/or careless organic farmers is modeled. Based on this calculus, a *heuristic model* to optimize inspection strategies is developed. The objective is to implement sanctions and inspection frequencies in a way that the net social cost arising from farmers' non-compliance with an organic standard will be minimized. Net social cost depends on present and future social damages linked to non-compliance and on the cost resulting from control efforts. We analyze the interplay of important factors that need to be considered when planning inspection strategies. This analysis is performed using *Monte Carlo simulations* for several scenarios combining different damage functions, fines and compliance cost distributions. The simulations show that even without fines a situation can arise where a large proportion of operators comply. This can facilitate enforcement and reduce social cost.

Keywords: Organic farming standard, enforcement, economics of crime, optimized control system

Acknowledgement: This article was generated 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. The article 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. The authors thank all colleagues in the CERTCOST consortium who commented on earlier versions of this article. Special thanks for highly valuable comments in this context go to Danilo Gambelli, Ulrich Hamm, Meike Janssen and Raffaele Zanoli. All remaining errors and mistakes are ours.

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[1] This chapter consists of an unpublished manuscript that is to be submitted to a scientific journal.

5.1 Introduction

A heuristic model is a rule-based model that helps to better understand reality. It is built upon theory and information sources that are only loosely connected and would not qualify as a direct representation of reality. In our case, the purpose of such a model is to understand the interplay of important factors that determine non-compliance and to approach optimum inspection strategies.

The objective of this article is to analyze enforcement measures designed to reduce the occurrence of non-compliance with an organic standard. Basically, this analysis must be accomplished by considering the compliance costs arising at the farm level, the possible social damages caused by non-compliance and the inspection and sanction efforts resulting from enforcement measures, which – in case they are effective – will influence the probability of detecting non-compliance. Hence, it must be taken into account that the incidence of non-compliance and related social damages can be influenced by deterring fines and further social sanctions as well as by inspection frequencies.

First, in chapter 5.2, by applying the theory of economics of crime, the decision of an opportunistic and/or inadvertent farmer to comply with a certain process standard is modeled. Second, in chapter 5.3, a heuristic model is developed, which is built upon the calculus model from chapter 5.2, and then used to optimize a control body's inspection strategy to reduce organic farmers' non-compliance. In chapter 5.4, for selected functional relationships and parameter settings, optimum inspection strategies are discussed using a ceteris paribus analysis. Chapter 5.5 contains our main conclusions regarding the elaboration and continuous adaptation of appropriate inspection strategies.

5.2 Theoretical model explaining organic farmers' non-compliance

Following the *economics of crime approach*[2] established by BECKER (1976) and STIGLER (1970), an economic model explaining organic farmers' non-compliance should reproduce for a given standard the main relationships between the factors mentioned in the introduction. Most notably, as in the case of other offences (cf. EHRLICH, 1974; EIDE, AASNESS AND SKJERPEN, 1994; ANTONY and ENTORF,

[2] For an overview on the economics of crime approach with special regard to compliance in agriculture, see HERZFELD and JONGENEEL, 2008, p. 3ff.

2002), the long-term relationship between inspection frequency and incidence of non-compliance should be negative. In addition, for other variables, sensible assumptions can be made regarding the direction of relevant effects.

At least part of the organic farmers considered should behave opportunistically in that they will make only minimal efforts to comply with the given organic standard or will even consciously cheat if the expected sanctions, due to detected non-compliance, are considered low when compared with the compliance cost. In our model approach, the compliance cost also contains different individual efforts required to obtain all information that is needed to fulfill the considered standard.

Hence, our starting point is from the perspective of a single organic farmer who tries to maximize her expected utility and who deliberately (i.e., opportunistically, in the original sense) or unconsciously (i.e., opportunistically due to carelessness) will infringe upon the standard when such action is deemed to be beneficial for her. For simplicity, our analyses are built upon the assumption of risk-neutrality. Thus, similar to the approach by ALMER and GOESCHL (2008, p.6f.), we assume a risk-neutral opportunistic farmer's decision either to comply with a certain organic standard or not as determined by the following inequality. If

$$H[B|NC_{it}=1]=C_t\left(s_i;fs_i;ft_i;fe_i;fl_i\right)-P_d\left(s_i,fs_i,ft_i,IF_{t-1},IR_{t-1}\right)P_s\left(SF_{t-1}\right)\Big(F+L\Big(s_i,fs_i,ft_i,d\left(fl_i\right)\Big)\Big)+\varepsilon_{it}>0 \tag{5.1}$$

then NC_{it} = 1, NC_{it} = 0 otherwise, with

H[.] = Expectation of .
t = time period (year)
i = farm number (i = 1, …, n)
$B|.$ = Net benefit given .
NC = Non-compliance (NC_{it} = 1 if farmer i does not comply at time t, NC_{it} = 0 otherwise)
C = Compliance cost saved when infringing upon the standard and which depends on
- *s* = site (location of the farm)
- *fs* = farm size (e.g., measured in UAA of the farm)
- *ft* = farm type (e.g., dairy farm or arable farm)
- *fe* = farmer's experience (e.g., measured in years of organic farming practice)
- *fl* = farmer's liquidity

P_d = (Subjective) probability of being detected in the case of non-compliance depending

on *s*, *fs*, *ft* as well as on
IF = (perceived) inspection frequency and
IR = (perceived) inspection rigor (e.g., determined by inspection duration and accuracy observed during former inspection visits)
P_s = Probability of being sanctioned when detected, which depends on
SF = (perceived) sanction frequency in the case of detected non-compliance
F = Fine related to the sanction (assumed to be given and constant over time)
L = Present value of future profits lost due to sanction-related marketing restrictions, which depend on *s*, *fs* and *ft* as well as on
d = discount rate (also influenced by the farmer's liquidity *fl*)
ε_{it} = error term reflecting further individually different costs and/or benefit-determining factors, such as the "warm glow" discussed herein, as well as a random error.

We must address an *incentive constraint*, which, in our case, is fulfilled when inequality (5.1) is negative, thus motivating farmers already in the organic farming business to comply with the agreed standard. We assume that the *participation constraint* is fulfilled in either case, which means that organic farmers' utility derived from correctly farming organically is always greater than the respective reservation utility, which for instance, could be the expected profit from conventional farming (for a general explanation of incentive and participation constraints in principal agency theory, see FURUBOTN and RICHTER, 2005, p. 206ff.).

Inequality (5.1) is intended for a situation in which farmers have an interest to stay in the organic business, as they expect future profits from farming organically and selling their produce as organic. Otherwise, *L* in the above inequality would be zero. In other words, L is the present value of a so-called *reputation rent* that can be lost if cheating is detected. In this sense, our approach differs from standard economics of crime, as we are incorporating elements of the theory of self-enforcing agreements according to which a „firm will honor its implicit quality contract as long as the difference between the capital values of the noncheating and cheating strategies […] is positive" (KLEIN and LEFFLER, 1981, p. 622) in our model (for a similar application in the context of food safety standard enforcement, cf. LIPPERT, 2002). A possible direct sanction (fine *F*) is increased by an indirect sanction because of additional market sanction-related losses *L*.

Consequently, the following model does not apply to anonymous fraudulent actors who just sell their conventional produce as organic and then disappear from the market (i.e., a "hit and run" strategy). In practice, the amount of *L* is a farm individual expectation value depending, among other things, on the quantity of future produce excluded from organic marketing due to a certain standard non-compliance as well as on the corresponding time span during which organic marketing will be prohibited. In the case in which a batch of cheese has been incorrectly labeled this time span will only cover a few days, whereas it may extend to “eternity” in a case of deliberate severe non-compliance such as the large-scale use of forbidden pesticides.

In organic agriculture, some rules’ compliance costs, C_i, are likely to strongly vary over the years depending on weather conditions. For instance, a humid spring that leads to increased pressure from fungal plant diseases could strongly increase opportunity cost, C_i, which consists of profit reductions when renouncing forbidden fungicides.

Notice that compliance costs, C_i, do not only contain opportunity and/or production costs directly resulting from observing the specific organic standard, but they also contain information and transaction costs that must be borne because compliance implies being well informed about the corresponding process standard. The individual information costs depend, among other things, on the education and the cognitive faculty of every farmer i. In this sense, careless, non-compliant farmers (who apparently do not consciously cheat) can also be considered to be implicitly acting according to inequality (5.1). Because they were inaccurate, they unconsciously evaluated costs, C_i, which incorporate the cost for obtaining all information necessary for accuracy, as greater than the expected losses due to possible sanctions.

Furthermore, again depending on the personality of the respective farmer, costs, C_i, may be more or less reduced due to the good feeling – the “warm glow” – linked to compliance with the organic standard. For some farmers, the monetary equivalent of this “warm glow” may be so high that they will never cheat regardless of how high the compliance costs. These farmers are clearly non-opportunistic. Consequently, a given group of farmers may consist of two subgroups: non-opportunistic farmers for whom NC_{it} is always zero and opportunistic farmers who will continuously ponder their behavior according to inequality (5.1).

Then, let x be any factor that determines the magnitude of the net benefit, Bt, of a given type of non-compliance that when detected and punished, entails direct and/or indirect sanctions. Thus, it follows that as long as

$$\frac{\partial B \big| NC_{it} = 1}{\partial x} = \frac{\partial B}{\partial x} > 0 \tag{5.2}$$

a relevant increase of the benefit determining factor *x* will lead

(i) to a higher probability *P*(*NCit* = 1) that a certain farmer *i* does not comply with the corresponding standard and

(ii) to a higher overall number of non-complying farmers (*NCF*) as inequality (5.1) will become positive for more opportunistic farmers.

Because

$$\frac{\partial B}{\partial P_d} = -P_s(.)\big(F + L(.)\big) < 0 \tag{5.2a}$$

the number of non-complying farmers, *NCF*, should decrease with the probability of being detected in the case of non-compliance. The same holds for the effect of the inspection frequency, as

$$\frac{\partial B}{\partial IF_{t-1}} = -P_s(.)\big(F + L(.)\big)\frac{\partial P_d(.)}{\partial IF_{t-1}} < 0 \quad \left(\textit{because} \quad \frac{\partial P_d(.)}{\partial IF_{t-1}} > 0\right). \tag{5.2b}$$

According to inequality (5.1), an increased monetary value of sanctions will entail a decline in the number of non-complying farmers, *NCF*, because

$$\frac{\partial B}{\partial\big(F + L\big)} = -P_d\ P_s < 0. \tag{5.2c}$$

5.3 Model for the optimization of inspection strategies to reduce organic farmers' non-compliance

According to the microeconomic theory as treated in this chapter in section 5.3.1, we will briefly outline a general model structure that illustrates the interactions and implications of important factors that impact the minimization of the social cost related to non-compliance. Here, the main objective is to illustrate the structure of the problem. To derive quantitative recommendations from such a model for specific standard and inspection situations would require the quantification of its parameters and functional relationships. In section 5.3.2, we develop a simplified heuristic model that – using rough assumptions for parameters and social damage functions – allows for analyzing the interplay of important factors that need to be considered when designing inspection strategies.

5.3.1 General model structure

Our normative analysis of organic farming control measures is based on the idea that a control body should implement a combination of sanctions and inspection frequencies in such a way that the resulting incidence of non-compliance will be socially optimal (for a background, cf. BECKER, 1974; BECKER, 1976; PYLE, 1983; for an application to food safety performance standards, cf. LIPPERT, 2002).

In the following, we consider a group of n_k organic farmers who share the same site conditions, *s*, and farm type, *ft*, and whose farms are characterized by a similar farm size, *fs,* as well as similar organic farming experience *fe*. However, the members of this group are different with respect to some other individual attributes that are difficult to observe such as the availability of liquid assets and present values of future profits lost due to possible sanctions, *L*. The corresponding characteristics determine the differences in compliance behavior within the group. $NCF_{k\ t} \leq n_k$ is the number of non-complying farmers at time *t* within the group.

Notice that the inspections considered in our model are spot checks that verify whether a certain well-specified standard has been observed. These checks occur during a given period of time *t*. Their frequency lies between 0 (i.e., no inspection visit at all) and 1 (i.e., all farms n_k are inspected within period *t*). A further simplification consists of the isolated consideration of different organic farming rules, which means that we do not consider all of the rules to be met when farming organically but only single rules such as the interdiction of chemical fertilizers, the banning of certain pesticides or the implementation of specific bookkeeping duties. Such a separated consideration of the rules is necessary because of the varied magnitude of the related damages. Damages resulting from an infringement of bookkeeping duties are rather small, whereas ecological and (sectoral) social damages linked to the use of a forbidden pesticide can be enormous.

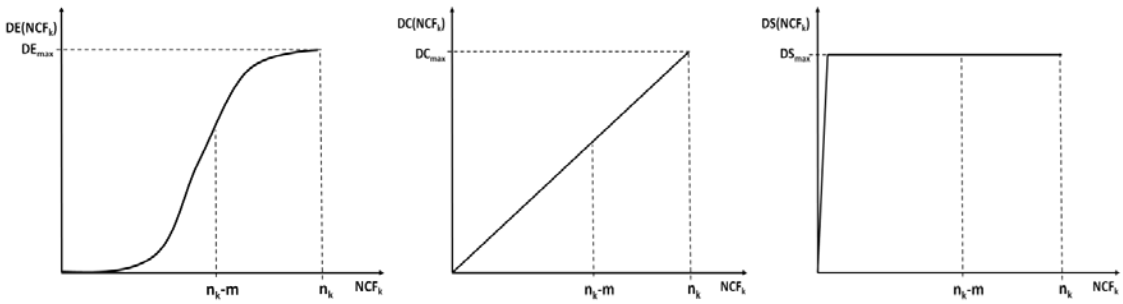
With respect to the social damage generated by the breach of a specific organic standard or rule, we distinguish three different categories:

$DE(NCF_{k\ t}) =$ *Ecological damage* resulting from foregone positive externalities linked to compliance with the considered standard,

$DC(NCF_{k\,t})$ = *Consumer damage* to be borne by the purchasers of organic products who (ignorantly) do not receive the product for which they actually paid and

$DS(NCF_{k\,t})$ = *Sectoral damage* resulting from diminished total revenues of the entire organic sector because of loss of consumer trust when a standard breach emerges.

Relevance, size and marginal damage strongly differ for the different categories depending on the organic product and the standard or rule considered. For the first category, it seems plausible to assume a cubic damage function as the one displayed in *Figure 5.1a*, which means marginal *Ecological damage (DE)* – for example, due to pesticide emissions – increases with the number of non-complying farms until a certain point and then declines until a maximum damage is reached. With only several non-complying farms, the marginal ecological damage is relatively low because of natural buffer capacities. With many non-compliers, the environment may be already so strongly degraded that a further non-complying farm would not add much additional harm.



(a) (b) (c)

DE = Ecological damage, DC = Consumer damage, DS = Sectoral damage, NCF_k = number of non-complying farmers, n_k = number of all organic farmers in the group, m = number of always complying organic farmers and $D._{max}$ = maximum possible damage in the respective category – Further explanations in the text.

Fig. 5.1 Examples for possible social damage functions

Consumer damage (*DC*) occurs either when a purchaser unwittingly consumes faulty food items, that is, products that do not have the characteristics paid for that are from undetected non-complying farms or when, as a consequence of detected non-compliance, such items are marketed at the lower price for conventional produce. In the latter case, the corresponding marginal damage could be estimated based on the price difference between the organic and the conventional product. In the former case, the related marginal damage is difficult to assess as it may be different for each consumer. For instance, some consumers may valuate the harm from food that contains certain pesticide residues relatively high while others may see harm to be much less problematical. As it cannot be established whether a defective product will be consumed by somebody who valuates this fact more or less seriously, a constant marginal damage is assumed, leading to a linear damage function, as the one shown in *Figure 5.1b*. In some cases, the corresponding marginal damage could be derived from the price differences between faultless (organic) and faulty (conventional) products. Due to the fact that some individuals have a willingness to pay that exceed organic market prices, such an estimate would be a lower bound of the true social damage $\partial DC(NCF_k)/\partial NCF_k$.

An important *sectoral damage* (*DS*) can occur when non-compliances with a rule, such as the ban of certain pesticides, are not detected on the farm in time period *t* but are revealed later in time period *t+1* due to the supervision activities of traders or, in extreme cases, because of people becoming ill. In such cases, just one non-complying farm not duly excluded from organic business could result in a complete loss of consumer trust in the organic farming business. As consumer trust is an important prerequisite for obtaining premium prices in the organic sector (cf. GIANNAKAS, 2002; JANSSEN and HAMM, 2011), the resulting expected social damage would consist of the sector's diminished total revenues along with future income possibilities lost due to the respective "scandal". "Expected" in this context means that the assumed sectoral damage must be multiplied by the (subjective) probability that the non-compliance related scandal actually occurs. For important organic rules, such as pesticide bans, the sectoral damage function is likely to resemble the one displayed in *Figure 5.1c*: only a few, or even one, non-complying farmer may cause maximum possible sectoral damage.

Considering both the social damages linked to non-compliance $D.(NCF_{k\,t})$ and the control body's costly inspection and sanction effort E_t (expressed in monetary units), the objective is to optimize the $NCF_{k\,t}$. Therefore, from the perspective of a governmental authority or a control body acting on behalf of the entire society and assuming that the fine *F* is imposed if there is detected non-compliance, the following net social cost *G* has to be minimized (symbols used as introduced above and defined in the annex):

$$G = DE\left(NCF_{kt}\right) + DC\left(NCF_{kt}\right) + DS_{t+1}\left(\left[1 - P_d\left(IF_t, IR_t\right)\right] NCF_{kt}\right) + E_t\left(IF_t, IR_t, SF_t\right) - P_d\left(IF_t, IR_t\right) SF_t \; NCF_{kt} F \text{ min!} \tag{5.3}$$

with

$$NCF_{kt} \quad = NCF_{kt}\left(P_d\left(IF_{t-1},\ IR_{t-1}\right), P_s\left(SF_{t-1}\right), F\right) \tag{5.4}$$

where $DS_{t+1}(.)$ is the discounted future sectoral damage resulting from non-complying farms not detected in time period t.

Merging DE and DC as DEC and assuming an interior solution for a steady-state situation (where, for all relevant variables, the optimized values $v = v_{t+1} = v_t = v_{t-1}$), the following first order conditions must be fulfilled:

$$\frac{\partial E(.)}{\partial IF} - \left[\frac{\partial P_d(.)}{\partial IF} NCF_k + P_d(.) \frac{\partial NCF_k}{\partial P_d} \frac{\partial P_d}{\partial IF}\right] SF \; F = \tag{5.5a}$$
$$= -\frac{\partial DEC}{\partial NCF_k} \frac{\partial NCF_k(.)}{\partial P_d} \frac{\partial P_d(.)}{\partial IF} + \frac{\partial DS}{\partial(.)}\left[\frac{\partial P_d}{\partial IF} NCF_k - \left(1 - P_d(.)\right) \frac{\partial NCF_k(.)}{\partial P_d} \frac{\partial P_d(.)}{\partial IF}\right]$$

$$\frac{\partial E(.)}{\partial IR} - \left[\frac{\partial P_d(.)}{\partial IR} NCF_k + P_d(.) \frac{\partial NCF_k}{\partial P_d} \frac{\partial P_d}{\partial IR}\right] SF \; F = \tag{5.5b}$$
$$= -\frac{\partial DEC}{\partial NCF_k} \frac{\partial NCF_k(.)}{\partial P_d} \frac{\partial P_d(.)}{\partial IR} + \frac{\partial DS}{\partial(.)}\left[\frac{\partial P_d}{\partial IR} NCF_k - \left(1 - P_d(.)\right) \frac{\partial NCF_k(.)}{\partial P_d} \frac{\partial P_d(.)}{\partial IR}\right]$$

$$\frac{\partial E(.)}{\partial SF} - P_d\left(IF_t \; IR_t\right)\left[NCF_k + SF \frac{\partial NCF_k(.)}{\partial P_s} \frac{\partial P_s(.)}{\partial SF}\right] F \quad = \tag{5.5c}$$
$$= \quad -\frac{\partial DEC}{\partial NCF_k} \frac{\partial NCF_k(.)}{\partial P_s} \frac{\partial P_s(.)}{\partial SF} - \frac{\partial DS}{\partial(.)}\left[\left(1 - P_d(.)\right) \frac{\partial NCF_k(.)}{\partial P_s} \frac{\partial P_s(.)}{\partial SF}\right].$$

Condition (5.5a) implies that in the optimum, the marginal cost of increasing the inspection frequency $\partial E(.)/\partial IF$ minus the increase in captured fines related to the marginal change ∂IF should be equal to the resulting reduced social damage plus the avoided future damage due to additional detection of non-compliance. Condition (5.5b) can be interpreted similarly with regard to the marginal cost of increasing the inspection rigor $\partial E(.)/\partial IR$. Condition (5.5c) indicates that the marginal cost of increasing the sanction frequency in case of detected non-compliance $\partial E(.)/\partial SF$ minus the resulting increase in captured fines should be equal to the reduced social damage caused by the deterring effect of the marginal change ∂SF.

The right-hand side of condition (5.5a) illustrates that an increase in the inspection frequency may have two damage reducing effects: an *indirect* effect resulting from deterrence (less *DEC* and *DS* because of fewer non-complying organic farmers as more farmers will comply with the standard due to higher expected sanctions) and a *direct* effect because, in the future, less faulty organic production will be brought to the market as more non-complying farms are found today (i.e., reduced *DS*).

Furthermore, following the idea already put forward by JEREMY BENTHAM in 1823 (1907, p.171, p.175) that an offender's harm due to punishment should not exceed the damage to be avoided, from an overall social point of view, constraint

$$P_d\left(IF, IR\right)\cdot P_s\left(SF\right)\cdot\left[F + L_{MNC}\right] \leq \frac{\partial DEC}{\partial NCF_{k\; n_{MNC}}} + \left(1 - P_d\left(IF, IR\right)\right)\cdot\frac{\partial DS}{\partial NCF_{k\; n_{MNC}}} \tag{5.5d}$$

should be observed. Thus, the expected non-complying farmer's loss due to the sanction (corresponding to compliance cost C_{MNC} of the marginal offender $i = n_{MNC} \leq n_k$, according to (5.1) should be less or equal to the related expected marginal damage caused to other members of the society.

5.3.2 Simplified heuristic model

To simplify the problem, it is assumed that in the analyzed steady state, $P_d(IF) = IF$ such that $\partial P_d/\partial IF = 1$. The further simplification of assumptions affects both inspection rigor *IR* and sanction frequency in the case of detected non-compliance (in the following, $P_s = SF = 1$), which are supposed to be given and cannot be influenced. Consequently, conditions (5.5b) and (5.5c) are not relevant in the following.

Next, for simplicity, we neglect consumer damage *DC* and imagine a situation in which the non-compliance does affect the environment but does not affect the material food qualities (e.g., forbidden pesticide use, which reduces biodiversity but does not lead to residues in food). Hence, we can set the constant marginal damage $\partial DC/\partial NCF_k = 0$.

In the scenarios in which it is relevant, the sectoral damage, *DS*, will be modeled as represented in *Figure 5.1c*, indicating that for the first few non-complying farms there will be a rather significant marginal damage. Thus, DS_{max}, which could be the difference in sales revenues from marketing the entire organic sectors' produce either organically or conventionally, may be reached relatively soon. It only takes several non-complying farms being detected by traders, journalists or other actors to lose consumer trust and completely ruin the organic market. The social damage, DE, will continuously increase with the number of non-complying farmers. It should be zero at $NCF_k = 0$, and it will reach its maximum at $DE(n_k) = DE_{max}$. For the reasons previously cited, we assume a cubic damage function (i.e., initially increasing, later decreasing marginal damage, see *Figure 5.1a*). When $DE(0) = 0$, $DE(n_k) = DE_{max}$ and $\partial DE(0)/\partial NCF_k = \partial DE(n_k)/\partial NCF_k = 0$, this function can be written as

$$DE\left(NCF_k\right) = 3\frac{DE_{\max}}{n_k^2} NCF_k^{\;2} - 2\frac{DE_{\max}}{n_k^3} NCF_k^{\;3}. \tag{5.6}$$

In practice, if available, a rough estimate of the damage, DE_{max}, could be the difference between society's willingness to pay for the higher biodiversity linked to n_k farms farming organically.

A simple way to model a control body's inspection cost for a given inspection rigor, IR, as well as a given sanction frequency, SF, is to assume

$$E\left(IF \middle| IR, SF\right) = E\left(IF\right) = c_v\ n_k\ IF \quad => \quad \frac{\partial E(.)}{\partial IF} = c_v\ n_k \tag{5.7}$$

with c_v = cost per inspection visit.

When making assumptions for the necessary parameters, it should always be assumed that the average compliance costs, μ_C, do not exceed the average social damage per non-complying farm (DEC_{max}/n_k), as otherwise – according to the reasoning leading to inequality (5.5d) – the corresponding standard would not be reasonable from a social point of view. When building a sensible heuristic model, also the magnitudes of the possible future farm losses, L, in the case of detected non-compliance as well as inspection costs, c_v, and the fine, F, should be reasonably related to the average damage, DEC_{max}/n_k.

Next, the relationship between the equilibrium probability of being detected when not complying with the standard and the number of offenders $NCF_k(P_d)$ must be modeled. This modeling is achieved using *Monte Carlo experiments*. For this purpose, m members of the group of n_k farmers are assumed to be always honest and perfectly informed. Consequently, they will always comply with the considered organic standard no matter how disadvantageous this may seem for them, whereas the remaining $n_k - m$ farmers within the group will act opportunistically. According to inequality (5.1), an opportunistic farmer's compliance costs, C_i, and her expected overall losses, $P_d \cdot (F+L_i)$, when being detected as non-compliant determine whether she will comply with the standard (see corresponding inequality (5.1b), below).

In the following, the variables L_i and C_i are assumed to be normally distributed. Note, again, that a relatively broad range of possible costs, C_i, may also cover the high compliance costs of inadvertent or careless farmers who do not cheat consciously but who make mistakes because they do not know how to fulfill the required rules (see chapter 5.2). If they seriously tried to comply, it would lead to relatively high individual transaction costs incurred when gathering the necessary information. "Non-compliers by inadvertence" do not have (or want) to bear these costs. In every model run, using the assumed normal distributions, random values for L_i and C_i are drawn. Then, every risk-neutral opportunistic farmer i (i = 1, …, $n_k - m$) checks for the given fine, F, at *every* probability P_d between 0 and 1 whether

$$P_d \cdot \left(F + L_i\right) - C_i < 0\,. \tag{5.1b}$$

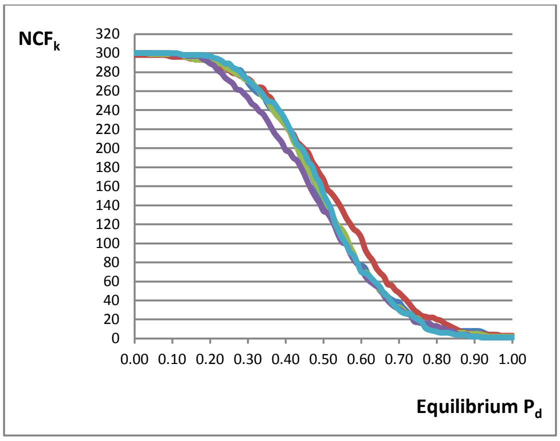
Those farmers for whom (5.1b) is negative will be non-compliers ($NC_i = 1$). Summing up all non-compliers at different probabilities, P_d, yields a curve, $NCF_k(P_d)$, that is used to calculate the respective net social damages, $G(P_d)$, as defined in equation (5.3).

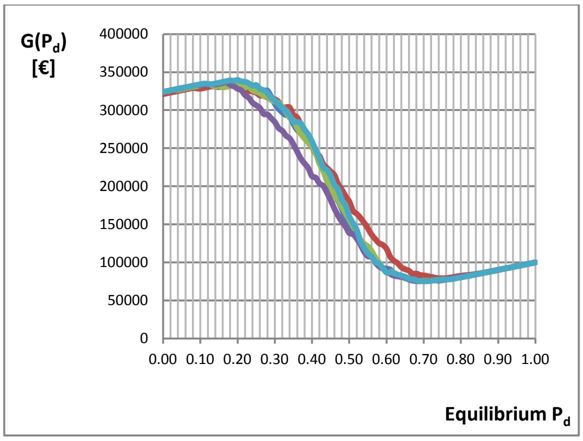
5.4 Model simulations to identify optimum inspection strategies under different scenarios

For every scenario, five Monte Carlo simulations are performed. In each simulation run, $n_k - m$ combinations of C_i and L_i are drawn from the two normal distributions $\Phi(C_i)$ *and* $\Phi(L_i)$. Then, for 100 probabilities between 0 and 1, each farm i is assigned its compliance status according to inequality (5.1b). Finally, for every run, the curves $NCF_k(P_d)$ and $G(P_d)$ can be displayed. The latter curve will be used to approximate the optimum inspection frequency for the set of assumed parameters in the respective scenario.

To implement a heuristic model, sensible values that warrant realistic ratios between the different parameters introduced must be assumed. For the simulations of the reference scenario, we set a total of n_k = 500 farms of which m = 200 are always complying with the considered standard. The maximum possible damage, DE_{max}, is 500,000 €. Furthermore, in the reference scenario, we set F = 0 € (i.e., no fine in the case of detected non-compliance), c_v = 200 € and the average compliance cost, μ_C = 800 €; the average loss L is μ_L = 1,600 €. Initially, the standard deviations are set to σ_L = 160 € and σ_C = 250 €. A cubic damage function corresponding to equation (5.6) and *Figure 5.1a* is used.

In the *reference scenario*, the possible future sectoral damage is neglected (i.e., $DS(.)$ = 0). The resulting curves $NCF_k(P_d)$ and $G(P_d)$ for the five runs of the reference scenario are shown in *Figures 5.2a* and *5.2b*.





Model parameters for the ***reference scenario***:
$P_d(IF) = IF$; SF = 1; n_k = 500; m = 200; DE_{max} = 500,000 €; c_v = 200 €; μ_L = 1,600 €; σ_L = 160 €;
$\boldsymbol{DS_{max}}$ **= 0 €; $\boldsymbol{\partial DS/\partial NCF_k}$ = 0 €; $\boldsymbol{\mu_C}$ = 800 €; $\boldsymbol{\sigma_C}$ = 250 €**; F **= 0 €**.

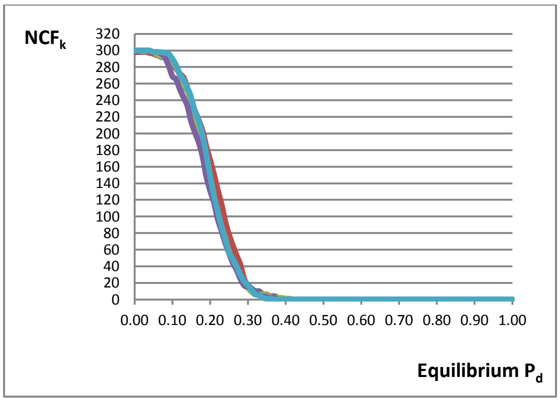
Fig. 5.2a Number of non-complying farms NCF_k depending on detection probability P_d

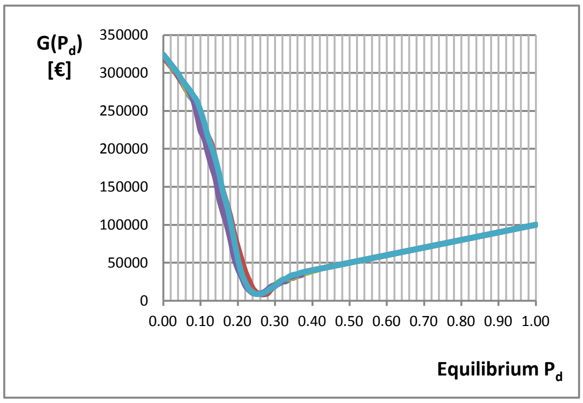
Fig. 5.2b Net social cost G (equ. (5.3)) depending on detection probability P_d

Depending on the run, the optimum inspection frequency corresponds to approximately 74%, and the corresponding minimized net social cost is between 75,000 and 80,000 €. In the optimum, between 18 and 30 non-complying farms would be accepted by the control body. However, if, in addition, restriction (5.5d) was to be observed, the inspection frequency could be lowered to approximately 56% until the damage, $\partial DE/\partial NCF_k$, of the marginal non-complying farm (except for run 2 $NCF_k \approx 100$ in this case) exceeds $P_d\ \mu_L$ = $0.56 \cdot 1{,}600$ = 896 € (which is a rough estimate of the marginal offender's expected loss). In doing so, inspection costs could be saved while the resulting additional damage, DE, which leads to an increase of $G(P_d)$, would be overcompensated by the saved compliance costs of the additional non-complying farmers.

Next, in *scenario I*, a fine of F = 2,400 € in the case of detected non-compliance is introduced. All other parameters are kept constant, and again the corresponding Monte

Carlo simulation is performed five times, which leads to the results displayed in *Figures 5.3a* and *5.3b*.





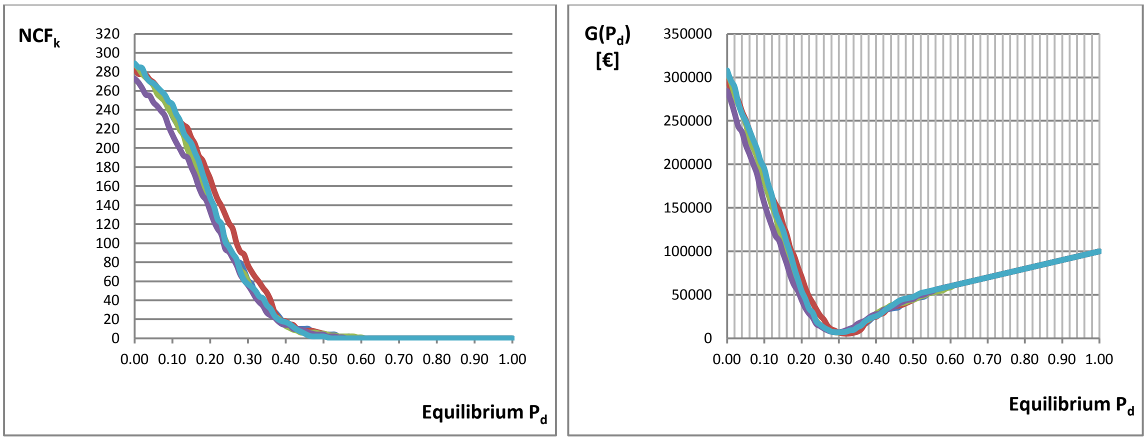
Model parameters for ***scenario I***:
$P_d(IF) = IF$; $SF = 1$; $n_k = 500$; $m = 200$; $DE_{max} = 500{,}000$ €; $c_v = 200$ €; $\mu_L = 1{,}600$ €; $\sigma_L = 160$ €;
$\boldsymbol{DS_{max} = 0}$ **€;** $\boldsymbol{\partial DS/\partial NCF_k = 0}$ **€;** $\boldsymbol{\mu_C = 800}$ **€;** $\boldsymbol{\sigma_C = 250}$ **€;** $\boldsymbol{F = 2{,}400}$ **€.**

Fig. 5.3a Number of non-complying farms NCF_k depending on detection probability P_d

Fig. 5.3b Net social cost G (equ. (5.3)) depending on detection probability P_d

In *scenario I*, the optimum inspection frequency is approximately 25%, and the corresponding minimized net social cost is approximately 9,000 €. In the new optimum, there would exist more (≈ 60 except for run 2) non-complying farms. Nevertheless, the net social cost is much lower than in the reference scenario because the expected fines and the inspection costs saved over-compensate the damage caused by the additional non-complying farmers. However, in this context, it should be considered that fines are not social benefits but merely a transferred welfare. Again, observing restriction (5.5d), the inspection frequency could be further reduced, but only slightly, to approximately 22% or 23%.

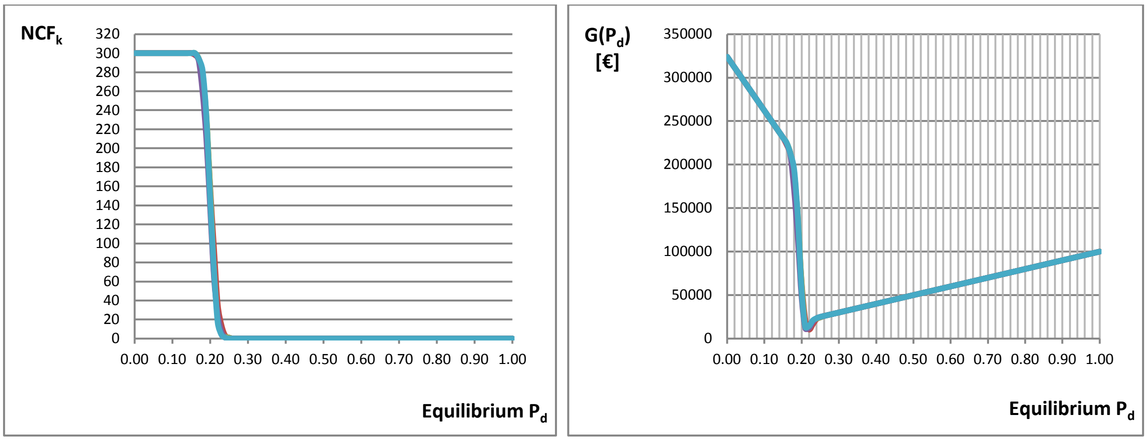
While maintaining all other parameters from scenario I in the following two scenarios, we vary the standard deviation of compliance cost σ_C. *Figures 5.4* (*scenario II*, high σ_C) and *5.5* (*scenario III*, low σ_C) reflect the resulting effects on the number of non-complying farms and on net social costs. Obviously, when opportunistic farmers are rather homogeneous regarding their compliance costs (i.e., low σ_C) an optimum detection probability is easier to find. In addition, close to this optimum detection probability, an increase in inspection frequency is more effective in this case.



Model parameters for ***scenario II***:
$P_d(IF) = IF$; $SF = 1$; $n_k = 500$; $m = 200$; $DE_{max} = 500{,}000$ €; $c_v = 200$ €; $\mu_L = 1{,}600$ €; $\sigma_L = 160$ €;
$\boldsymbol{DS_{max} = 0}$ **€**; $\boldsymbol{\partial DS/\partial NCF_k = 0}$ **€**; $\boldsymbol{\mu_C = 800}$ **€**; $\boldsymbol{\sigma_C = 500}$ **€**; $\boldsymbol{F = 2{,}400}$ **€**.

Fig. 5.4a Number of non-complying farms NCF_k depending on detection probability P_d

Fig. 5.4b Net social cost G (equ. (5.3)) depending on detection probability P_d

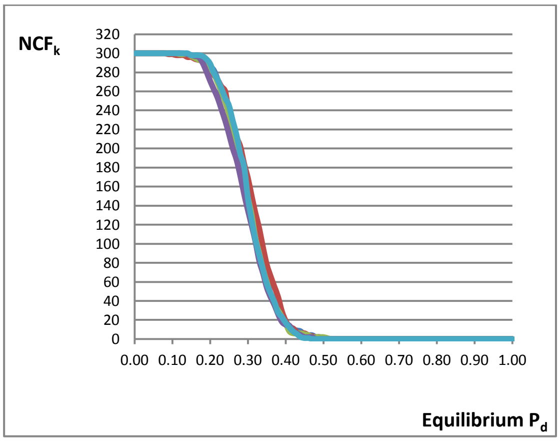


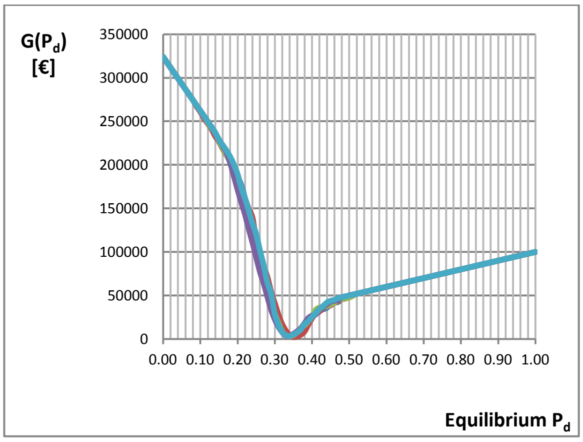
Model parameters for ***scenario III***:
$P_d(IF) = IF$; $SF = 1$; $n_k = 500$; $m = 200$; $DE_{max} = 500{,}000$ €; $c_v = 200$ €; $\mu_L = 1{,}600$ €; $\sigma_L = 160$ €;
$\boldsymbol{DS_{max} = 0}$ **€**; $\boldsymbol{\partial DS/\partial NCF_k = 0}$ **€**; $\boldsymbol{\mu_C = 800}$ **€**; $\boldsymbol{\sigma_C = 50}$ **€**; $\boldsymbol{F = 2{,}400}$ **€**.

Fig. 5.5a Number of non-complying farms NCF_k depending on detection probability P_d

Fig. 5.5b Net social cost G (equ. (5.3)) depending on detection probability P_d

Especially with respect to organic crop farming, compliance costs for the fulfillment of certain rules may strongly vary between years. For instance, due to humid weather conditions during the growing season, the opportunity costs for renouncing certain banned pesticides could easily increase. In *scenario IV* (see *Figures 5.6*), we maintain all parameters assumed in scenario I except the average compliance cost, μ_C, for which we simulated an increase of 50%. As a consequence, in the model, the certification body's optimum inspection frequency increases from approximately 25% to roughly 34%. At the same time, minimized net social costs, as defined by equation (5.3), are reduced by more than 5,000 € because the increased ecological damages and inspection costs are overcompensated by expected revenues from fines. Despite the higher control frequency leading to an increase in farmers' expected fines and future income losses, the number of non-complying farmers increases from approximately 60 to 77.





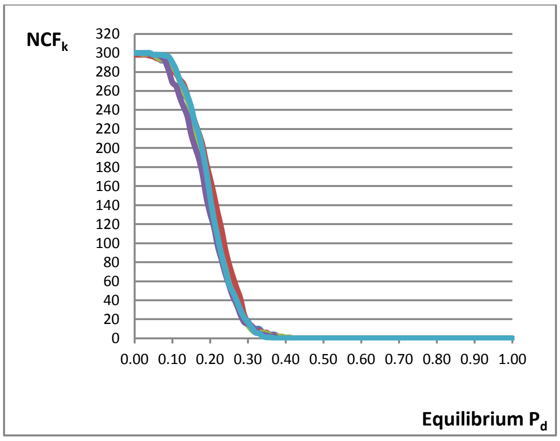
Model parameters for ***scenario IV***:
$P_d(IF) = IF$; $SF = 1$; $n_k = 500$; $m = 200$; $DE_{max} = 500{,}000$ €; $c_v = 200$ €; $\mu_L = 1{,}600$ €; $\sigma_L = 160$ €;
$\boldsymbol{DS_{max} = 0}$ **€**; $\boldsymbol{\partial DS/\partial NCF_k = 0}$ **€**; $\boldsymbol{\mu_C = 1{,}200}$ **€**; $\boldsymbol{\sigma_C = 250}$ **€**; $\boldsymbol{F = 2{,}400}$ **€**.

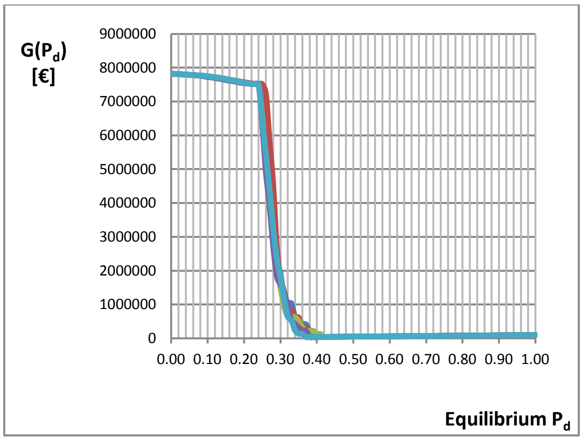
Fig. 5.6a Number of non-complying farms NCF_k depending on detection probability P_d

Fig. 5.6b Net social cost G (equ. (5.3)) depending on detection probability P_d

Finally, in *scenario V* (see *Figures 5.7*), we analyzed the effects of an important possible sectoral damage, *DS*, on optimized inspection frequencies and overall social costs. We assumed that for a fundamental organic rule, a hidden non-compliance of 10% (i.e., 50 non-complying model farms that are not detected during spot check controls) will eventually lead to a scandal that completely ruins the regional organic market for one year. Estimating a related damage, DS_{max}, of 7,500,000 €[3] and using a damage function such as the one displayed in *Figure 5.1c*, we obtain a marginal damage, $\partial DS/\partial NCF_k$, of 150,000 € per initially undetected non-complying farm when $(1 - P_d)\ NCF_k < 50$ and a marginal damage of zero otherwise. All other parameters are the same as in scenario I.

[3] The maximum potential sectoral damage DS_{max} should be related to the number and size of organic farms involved. In principle, it can be estimated from the organic sector's loss that would occur when its entire produce was sold at conventional prices instead of the higher organic market prices (i.e., the difference in corresponding sales revenues). Here, we assumed the entire sector consists of our n_k farms. A supposed per farm sales revenue difference of 15,000 € leads to a maximum sectoral damage of 15,000 times 500 = 7,500,000 € if the sector's entire organic produce has to be marketed conventionally.





Model parameters for ***scenario V***:
$P_d(IF) = IF$; $SF = 1$; $n_k = 500$; $m = 200$; $DE_{max} = 500{,}000$ €; $c_v = 200$ €; $\mu_L = 1{,}600$ €; $\sigma_L = 160$ €;
$\boldsymbol{DS_{max}} = \mathbf{7{,}500{,}000}$ **€**; $\boldsymbol{\partial DS/\partial NCF_k} = \mathbf{150{,}000}$ **€**; $\boldsymbol{\mu_C} = \mathbf{800}$ **€**; $\boldsymbol{\sigma_C} = \mathbf{250}$ **€**; $\boldsymbol{F} = \mathbf{2{,}400}$ **€**.

Fig. 5.7a Number of non-complying farms NCF_k depending on detection probability P_d

Fig. 5.7b Net social cost G (equ. (5.3)) depending on detection probability P_d

In scenario V, the optimum inspection strategy consists of extending the spot check controls until all farms comply with the respective standard. Depending on the run, this occurs in the model for inspection frequencies between 37% and 42% (instead of approximately 25% in the optimum of scenario I). Consequently, no ecological damage, *DE*, or sectoral damage, *DS*, occurs. Costs of inspection visits, not diminished by revenues from fines, are the only remaining social costs. Note that, given the farmers' good reactivity for the set of model assumptions analyzed in this scenario, it is not necessary to inspect all farms in order to make all farmers comply with the standard.

With a slight adaptation, the heuristic model developed thus far can be implemented by control bodies or authorities to analyze the implications of and to, at least approximately, optimize inspection strategies for groups of farmers in which the farmers within each group have a similar detection probability function $P_d(., IF)$.

5.5 Discussion and conclusion

In the next subsection we discuss possible model extensions. Then, we raise some caveats before concluding with suggestions to improve inspection strategies.

5.5.1 Possible model extensions

By broadening the horizon and looking beyond the inspection system, a further extension of the model could be the introduction of an additional probability, P_{in}, of being detected in the event of non-compliance *independent* of inspection frequency *IF* (e.g., due to whistle-blowers or because of hints from other parts of the supply chain). Then, the probability of being detected in the event of non-compliance would be

$$P_d\left(IF, P_{in}\right) = P_{in} + IF - P_{in} \cdot IF \quad = \quad IF + \left(1 - IF\right) P_{in} \,. \tag{5.8}$$

For simplicity, we assume that $F = \partial DS / \partial NCF_k = 0$ and *IR* and *SF* are given and constant over time. Then, entering $P_d(IF)$ from equation (5.8) into equations (5.3) and (5.4) and assuming, again, the existence of an interior solution for a steady state of minimized net social costs, the first order condition (5.5a) can be rewritten as

$$\frac{\partial E\left(.\right)}{\partial IF} = -\frac{\partial DEC}{\partial NCF^k} \frac{\partial NCF^k\left(.\right)}{\partial P_d}\left(1 - P_{in}\right). \tag{5.5a*}$$

Thus, in the case of decreasing marginal damage due to non-compliance and increasing marginal costs of inspection frequency, a rise in P_{in} reduces the optimum inspection frequency. P_{in} will be higher when the *traceability* of organic products is well established and warranted. However, the implementation or improvement of a corresponding system along the entire supply chain also entails costs in a way that a trade-off between further increasing the inspection frequency *IF* or the probability P_{in} must be faced. Consequently, under the assumptions above, a further optimum condition in addition to condition (5.5a*) must be considered

$$\frac{\partial E\left(.\right)}{\partial P_{in}} = -\frac{\partial DEC}{\partial NCF^k} \frac{\partial NCF^k\left(.\right)}{\partial P_d}\left(1 - IF\right). \tag{5.5a**}$$

Furthermore, risk-averse behavior could be modeled by adding a risk premium $r_i(P_d; F+L_i)$ to the left-hand side of inequality (5.1b). However, this addition would complicate the analysis as it implies assigning individual utility functions to the different farmers.

5.5.2 Caveats

As illustrated in chapter 5.4, the implementation or increase of fines can facilitate standard enforcement and reduce corresponding social costs. However, in practice, further transaction costs for related law suits and administration must be considered when trying to improve the efficiency of the certification system. Moreover, with respect to elevated fines, the fines may have an undesired effect on the participation constraint mentioned in chapter 5.2. Such an effect was not included in our heuristic model. That is, assuming a certain probability of being sentenced innocently, conventional farmers may refrain from converting to organic farming because the corresponding expected utility (reduced by expected unjustified fines) does not cover their reservation utility.

Our heuristic model incorporates the concept of self-enforcing agreements (see chapter 5.2), which implies that higher (expected future) prices for organic produce will increase the number of complying farms because of rising possible losses, L_i. Hence, in our model, greater price premiums for organic products are expected to reduce fraudulent behavior. However, in this context, it should be noticed that this conclusion is based on the specific market situation of organic farmers within a given region. There are many well-known farmers who cannot act anonymously. In another market situation, for example, when unknown traders attempt to sell their produce only once, high price premiums may have the opposite effect and attract more cheaters to the market.

Our model considerations are based on the concepts of opportunistic behavior and bounded rationality (for these concepts see FURUBOTN and RICHTER, 2005, p. 4f.), which means that people are supposed to act rationally given their limited information processing capacities. We did not include in our model clearly irrational or "crazy" behavior. In practice, this omission means that despite high expected sanction values along with low compliance costs, some non-compliance may still occur. Similarly, a sequence of unfortunate events may have such an effect. Thus, in the case of large possible damages, *DS*, it may be advisable to conduct further spot checks even if, in principle, every reasonable opportunistic farmer is supposed to comply for her own sake (for the situation outlined in *Figures 5.7*, this could mean to further extend inspections beyond a frequency of 42%).

Moreover, the socio-legal literature on compliance with regulations suggests that compliance behavior is not just determined by the fear of sanctions and rational self-interest (cf. AMODU, 2008). Among other factors, the general context and the design of regulations are important as are the inspectors' enforcement activities that go beyond imposed sanctions (AMODU, 2008). According to psychological literature, people are inclined to comply when the respective rules are perceived as fair and appropriate (cf. the literature quoted in HERZFELD and JONGENEEL, 2008, p. 8). In this context, a rule that does not make sense for the farmers or is seen as mere chicanery is less likely to be strictly observed.

5.5.3 Suggestions to improve inspection strategies

When planning efficient inspection strategies, possible social damages from standard infringements, costs of inspection measures and compliance costs dependent on the farmers' abilities to change their behavior should be considered. These factors must be balanced when choosing or updating inspection frequencies for the supervision of different organic rules (e.g., in the case of low social damage due to non-compliance but very costly inspection measures, corresponding spot checks or tests, if conducted at all, should be conducted rarely).

Due to differences in compliance costs and losses resulting from sanctions, as illustrated in chapter 5.2, different types of farms may demonstrate different compliance behaviors for the same rules and related possible damages. Thus, inspection frequencies should be targeted to farm types in such a way that a control body applies a higher inspection frequency when the respective farm category has shown a greater probability of non-compliance in the past. Only under the assumption of a farm-type independent detection probability, such a strategy means directing inspections towards farmers with a *truly* higher probability of non-compliance. Even if this assumption is not fulfilled, this approach would be sensible provided the control body is interested in directly avoiding sectoral damages (see DS_{t+1} in equation (5.3), section 5.3.1). When looking for factors that increase non-compliance or detection probability, control bodies may rely on adequate statistical modeling such as the use of discrete choice models.

A further reason for separating farms into relatively homogenous groups when designing inspection strategies is that, in such groups, the effects of different control strategies on farmers' compliance behavior are easier to assess (see chapter 5.4).

Inequality (5.1) in chapter 5.1 also illustrates that opportunistic farmers' expectations are based on previous experiences, thus suggesting that these farmers will adapt their compliance behaviors according to perceived past inspection and sanction frequencies. Consequently, a control body should adapt its inspection strategy, which could be done based on continuously up-dated discrete choice models that explain actual non-compliance probabilities. Furthermore, control bodies can occasionally vary the frequencies of unannounced inspections IF_t (some farmers are controlled more frequently and others less frequently) to gain a better understanding of how corresponding farms react (i.e., to approximate the effect $\partial NCF_k/\partial IF_{t-1}$).

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5.7 Annex: List of symbols used

H[.] = expectation of .
t = time period (year)
i = farm number ($i = 1, \ldots, n$)
$B|$. = net benefit given .
NC = non-compliance (1 if farmer *i* does not comply, 0 otherwise)
C = compliance cost saved when infringing upon the standard
s = site (location of the farm)
fs = farm size
ft = farm type
fe = farmer's experience
fl = farmer's liquidity
P_d = (subjective) probability of being detected in the case of non-compliance
IF = (perceived) inspection frequency
IR = (perceived) inspection rigor
P_s = probability of being sanctioned when detected
SF = (perceived) sanction frequency in the case of detected non-compliance
F = fine related to the sanction
L = present value of future profits lost due to sanction-related marketing restrictions
d = discount rate
ε_{it} = error term reflecting further individually different costs and/or benefit-determining factors
x = any factor that determines the magnitude of the benefit of a given type of non-compliance
$P(NC_{it}=1)$ = probability that a certain farmer *i* does not comply
NCF = number of non-complying farmers
n_k = number of organic farmers who share the same farm characteristics but are different regarding some individual attributes
NCF_k = number of non-complying farmers among the n_k farmers
m = number of always complying farmers among the n_k farmers
DE(.) = ecological damage resulting from lost positive externalities linked to compliance
DC(.) = consumer damage to be borne by the purchasers of organic products
DS(.) = sectoral damage resulting from diminished total revenues of the entire organic sector
DEC = *DE(.) + DC(.)*
$D._{max}$ = maximum possible damage in the respective damage category
G = defined net social cost resulting from non-compliance
v = optimized value for a certain variable
E = the control body's costly inspection and sanction effort expressed in monetary units
c_v = cost per inspection visit
n_{MNC} = index number of the marginal non-complying farmer ($1 \leq n_{MNC} \leq n_k$)
L_{MNC} = present value of future sanction-related losses of the marginal non-complying farmer
C_{MNC} = compliance cost of the marginal non-complying farmer
$\Phi(C_i)$ = probability density function of the $N(\mu_C, \sigma_C^2)$ normally distributed compliance cost C_i
μ_C = average compliance cost at farm level
σ_C = standard deviation of compliance cost at farm level
$\Phi(L_i)$ = probability density function of the $N(\mu_L, \sigma_L^2)$ normally distributed losses L_i
μ_L = average present value of future sanction-related losses at the farm level
σ_L = standard deviation of present value of future sanction-related losses at the farm level
P_{in} = probability of being detected independently from or outside of inspections in the case of non-compliance
r_i = risk premium assumed by farmer *i*

6 Synthesis and outlook

This final chapter intends to link the results that are presented in the preceding chapters in the format of journal articles. In the first section (6.1), emphasis is put on the specific characteristics of organic control data and the relevance of these peculiarities when analysing such data. This is also of relevance for supervision, to which the chapter 6.2 is devoted. The subsequent section presents the experiences gained when analysing non-compliance. These experiences then are considered in the heuristic model (6.4) that opens up the view and addresses control strategies from a system-view. The chapter concludes with an outlook on research suitable to extend the current work.

6.1 Characteristics of organic control data

Central parts of this thesis are based on the analysis of data originating from the organic control process, namely the chapters 2, 3 and 4. The quantitative analyses presented above, assume that potential biases are randomly distributed. The particular process of collecting organic control data can feature different biases, however. The following section illustrates and discusses different potential biases that could influence organic control data.

First, control data certainly are biased by an unknown dark figure. The dark figure consists of undetected non-compliant operators. Usual methods to asses dark figures in the area of business crime are not applicable (Bundesministerium des Inneren and Bundesministerium der Justiz, 2006). An important proxy for the dark figure are fraud cases detected outside the core organic control system, e.g., by general food and feed control, tax audits or by sample analysis in the organic food chain. Corresponding data that could illuminate the size of the dark figure exist at control bodies and supervisory institutions but were not available for this thesis.

Second, the data collection process is specific: every operator is controlled once, some operators however are controlled additionally due to the requirements of the regulation on the control frequency and the risk based control approach. This process corresponds to a complete survey of the universe which is complemented by an additional sample. If additional controls of an operator result in an overall higher detection probability of non-compliance, the results presented above could be biased by systematically different control frequencies.

Third, operators that are assessed as being more risky are probably not only more frequently, but are potentially also more thoroughly controlled. This would constitute a potential positive confirmation bias whose general relevance is documented (Jones and Sugden, 2001; Betsch, 2005). If such a positive confirmation bias is relevant for organic controls, this could experimentally be tested. Eliminating such a deep-rooted psychological mechanism from controls is difficult. However, such an effect could correlate with the individual characteristics of inspectors, which could be tested by detailed control data.

Fourth, it is reasonable to assume that different non-compliances exhibit different detectability. The data could be biased by higher detection probabilities and accordingly different dark figures that could correlate with specific production activities. Further analysis of non-compliances differentiating the area of non-compliance by detection frequency and sanction severity could examine this potential bias. Such analysis should integrate experts from the control sector. The detectability of non-compliance could also depend on the degree to which individual rules can be easily understood by operators and their acceptance of specific rules (Amodu, 2008). However, the latter effects are probably more relevant for minor non-compliances and not for the severe ones affecting organic integrity.

Fifth, organic operators can apply for exceptional permissions regarding specific rules of the regulation (e.g., tie-stalls usually are temporarily permitted under specific circumstances). The existence of exceptional permissions theoretically reduces the potential not to comply by excluding a specific rule. Data on exceptional permissions were not available for the studies presented but should be considered in future analyses of more detailed data.

Organic control data involve these biases which can only partially be considered in econometric modelling (e.g., the control frequency). The magnitude and relevance of these biases is thus largely unknown. This could present a fundamental criticism of the analyses presented. In future research, more detailed data and larger datasets (as well more records as longer time series) should be used and analysed in order to get a better understanding of the relevance and importance of the different biases.

6.2 Supervision of certification systems

Supervision is necessary to assure independent controls. It depends on reliable and valid data on operator characteristics, control characteristics, detected non-compliances, and imposed sanctions. These prerequisites are not yet sufficiently met. This could result from the characteristics of organic control data, discussed above, affecting the validity of the data. Missing reliability, however, results at least partly from missing definitions of the data to be reported.

The results of our analysis of German supervision data were intensively discussed with relevant stakeholders. We presented our study to different institutions, namely to representatives from the "*Bundesanstalt für Landwirtschaft und Ernährung*" (Federal Office for Agriculture and Food), who are responsible for collecting and merging the data on national level, representatives from the federal competent authorities and from different control bodies. The documented interest is an indicator for the practical relevance of this study.

Recently, the European Commission published a working document on "*official controls in the organic sector*" (European Commission - DG Agri, 2011) and the German Federal Ministry of Food, Agriculture and Consumer Protection (BMELV) presented a regulation on the approval of organic control bodies ("*Verordnung über die Zulassung von Kontrollstellen nach dem Öko-Landbaugesetz*" in the following "*ÖLG-Kontrollstellen-Zulassungsverordnung*") (BMELV, 2011). Both documents aim at a more harmonized implementation of the organic regulation on European and German level. The specification of categories of non-compliance together with a list of measures to be taken in case of non-compliance by the German act caused criticism as being too detailed and too complex (Neuendorff and Spiller, 2011). However, these documents prepare the ground for a more harmonized implementation that facilitates the comparability of data resulting from different control bodies. Thus, the guidelines and the regulation could result in a more reliable supervision of the organic control systems.

The gap of missing definitions of the central terms "*irregularity*" and "*infringement*" in the European organic regulation still exists today. This impedes the comparison of data on European level. The working document on organic controls does not alleviate this state, as this document is just a guideline, i.e. it is not legally binding[1]. The European organic regulation should be amended by clearly distinguishing different non-compliances (including also marginal non-compliances) and subsequent sanctions.

6.3 Analysis of non-compliance

The econometric analysis of non-compliance with an organic standard presented in this thesis is an approach that has not been used previously. Such methods could complement and enhance risk based control approaches not only in the area of organic certification, but also in other control systems.

The analyses of non-compliance consider Germany and Switzerland – two countries with different agricultural production conditions and different control systems (e.g., the German analysis refers to a public, the Swiss analysis to a private standard; see also Chapter 1.4.2 on the differences of the implemented sanction systems). Furthermore, the articles are based on different models. Therefore, the following synthesis of the results abstains from a comparative confrontation.

The econometric analyses are based on theoretical considerations and the formulation of hypotheses which are inferred from the "*Economics of Crime*" approach. Both analyses confirm some of the hypotheses. However, the results presented in this thesis do not yield a satisfactory overall picture of the factors contributing to non-compliance. This is reflected in the low Pseudo-R^2 values.

Nonetheless, the relevance of the main risk factors mentioned by the guidelines of the European Commission (European Commission - DG Agri, 2011) and the German handbook for organic control bodies (Fischer and Neuendorff, 2011) for the risk assessment are confirmed: previous sanctions, farm complexity (in terms of additional non-farm activities and livestock production complexity), and farm size. Other criteria suggested by either of the guidelines are also supported, however, not by both analyses likewise.

[1] The working document explicates: "*This document can not* [sic!] *be considered as a binding legal interpretation of the EU legislation, as such interpretation is the exclusive competence of the Court of Justice of the European Union*" (European Commission - DG Agri, 2011, p.4).

The impact of farm production characteristics (especially regarding crops) does not yield clear results: significant results appear only scattered in single years and partly are against the hypotheses (e.g., the effects of unutilised land). The heuristic model suggests grouping similar farm types due to their similar compliance costs and losses. This suggestion could also be considered in future econometric analyses: based on the detailed farm production data, the farms could be categorised into different farm types (such as arable crop farms, forage farms, mixed farms with/without livestock, cf. e.g., Zander et al. (2008)).

The supplied control data allowed only the thorough analysis of farm data. The control bodies, that provided the data, collected very detailed data on farms, but only little data on processors and other activities. However, even the farm data do not completely cover the criteria suggested by the Commission guidelines (European Commission - DG Agri, 2011) and the German handbook (Fischer and Neuendorff, 2011) on risk based control approaches. It could be possible that the observed disparity of data coverage between farm operators and non-farm operators is not representative. However, the private control bodies that provided the organic control data are of high market importance, nationally and internationally. Therefore, the observed disparity seems relevant. This shortcoming is also relevant for supervision issues, since the structure of the controlled operators and associated determinants for non-compliance with regard to processing and other production activities could not be further examined (see Chapter 2.4).

The results of the farm analysis point to the importance of operations' structural data. Therefore it could also be useful to collect such data on non-farm operators more systematically (for lists of data that could be collected, cf. European Commission - DG Agri, 2011; Fischer and Neuendorff, 2011).

The overall explanatory content of the models indicates the potential to improve the models by integrating further variables. This especially refers to personal characteristics of an operator, such as age, education, qualification, risk and environmental attitude, and criminal record. Also financial data of the farmer and the farm could be of specific relevance. The importance of the latter data is acknowledged by the German handbook. However, it is very difficult to get relevant and valid data in this area. Scientific research interest regarding most of the data mentioned probably conflicts with data protection issues and also the acceptance of organic operators.

The "*gut feeling*" of inspectors performing controls can be an important factor for detecting non-compliance. Although this thesis argues strongly for a further development of quantitative risk assessment, at the same time, it concedes the invaluable instinct of the inspector, who visits organic operations, talks to the responsible managers, and who observes the production process. Capturing this "*gut feeling*" by reliable indicators, could be a fruitful approach.

The inclusion of further data on farms' natural conditions, seasonal climate situation affecting production conditions or market data could also be an option to further elaborate quantitative risk assessment.

6.4 Heuristic model

The heuristic model considers the results of the preceding articles and – after the incipient supervision article – again adopts a societal view on the organic control system. This model not only illustrates the theoretical foundation of the econometric models in detail but especially considers the damage resulting from non-compliance and the cost of a control system. Hereby, the relevant parameters for optimising the control system are described. The Monte Carlo simulations highlight the important interrelations between the relevant parameters. The heuristic model can contribute to an optimisation of control strategies.

The organic certification market in Germany currently comprises 20 control bodies (BLE, 2012). Furthermore, 15 federal competent authorities supervise the implementation of the EU organic regulation. This plurality of actors framing and influencing control strategies complicates a harmonised and efficient implementation. However, the heuristic model implies an overall view on the control system and assumes a central control of important parameters.

The idea to centrally prescribe basic control requirements (e.g., number of additional controls, share of unannounced controls, and number of samples to be taken) expressed in the "*ÖLG-Kontrollstellen-Zulassungsverordnung*" therefore is reasonable. The draft of this regulation is in the process of enactment. The requirements defined by this regulation probably are – if at all – only based on rough economic considerations. Therefore, the implementation, the effectiveness as well as the costs of the implementation of this regulation must be monitored. The presented heuristic model can be a useful tool when evaluating and monitoring the "*ÖLG-Kontrollstellen-Zulassungsverordnung*".

6.5 Outlook

Organic controls are considered a prerequisite for the existence of organic markets. Currently, any technological or societal change that could supersede organic control in its actual shape seems far away: The technological development of procedures to authenticate organic food on the product[2], e.g., based on laboratory analyses, is at most in its infancy. A societal (e.g., by legislation) or demand change allowing or demanding only organic production methods could also supersede organic control, but is unrealistic at present. Therefore, the further development of organic control systems is the current challenge.

A report on effective inspection and enforcement in UK stated: "*Risk assessment […] is not implemented as thoroughly and comprehensively as it should be*" (Hampton, 2005). Presumably, this general statement on risk assessment applies for organic certification systems, too. The use of further developed econometric models for risk based control approaches implies potential advantages. Such a quantitative approach can positively complement the qualitative risk assessments currently applied. Potential advantages are the simultaneous analysis of different risk factors at once, the option to perform the analysis based on current data to capture seasonal effects, and the impartiality of the method.

Future corresponding analyses should specifically focus on the determinants of severe non-compliances jeopardizing organic integrity mostly. The rare occurrence of severe non-compliances requires much larger datasets. Such datasets are also needed to further investigate the potential biases discussed in chapter 6.1. The analysis of longer time series could allow capturing dynamic effects, e.g., how operators react to different control strategies and sanction behaviour. Then, count data models could also be a viable alternative opening up further opportunities.

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[2] This implies a rigorous change regarding the costs of quality information of organic food products. The existence of a corresponding affordable technology could lower information costs and uncertainty. This would mean that the process quality "*organic*" became a product quality.

If the application of such a quantitative risk analysis is adequately considered in the data selection and collection process of control bodies, this can improve risk based control systems. The application however requires considerable technical and methodological expertise and is far from being implemented in a standardized way in control data bases.

The evolution of data handling and software development (e.g., the spread of open-source software) could offer opportunities for the practical implementation of sophisticated risk based control systems. Major certification systems with a central database and large number of operators would present a good testing field for the further development. But even in the fragmented German control sector, it could be possible to develop and to implement an open-source database used conjointly by different control bodies. The open-source situation would allow sharing development costs and integrating expert knowledge on data handling and data analysis.

This thesis focuses on details of organic controls. Such controls however need to be communicated or signalled credibly to consumers. Consumers generally do not know the details of standards and the control system (Janssen and Hamm, 2011), but consumers trust or distrust individual labels. Different stakeholders of the organic control system such as control bodies or the competent authorities could partly alleviate this information gap. A possible approach could be that control bodies publish their control efforts and results yearly (cf. e.g., Rundgren (2009)) to make the control system more transparent. Such transparency could contribute to establish a reputation system (Jahn et al., 2005) for organic controls. Such measures could easily and at low cost be implemented by different actors in the control system.

Standards fulfil important functions in our economic life. This thesis sheds light on relevant aspects of control systems that shall assure the adherence to standards. This research focuses on the organic food market and illustrates the relevance of supervision and the further development of risk based control approaches. However, the approach presented, the methods applied, and the findings are also relevant for other food control systems in general.

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Hiermit erkläre ich, Alexander Zorn, dass die vorliegende Dissertation Ergebnis meiner eigenständigen wissenschaftlichen Arbeit ist und ich zur Fertigstellung dieser keine weiteren als die angegebenen Quellen und Hilfsmittel verwendet habe. Die verwendeten Quellen und Hilfsmittel sowie wörtlich oder inhaltlich übernommene Stellen sind als solche gekennzeichnet. Die Unterstützung einer kommerziellen Promotionsvermittlung oder -beratung habe ich nicht in Anspruch genommen. Außerdem wurde und wird die vorliegende Dissertation weder in Teilen noch in Gänze im Zuge anderer Promotionsverfahren verwendet.

Diese Arbeit ist im Rahmen des Forschungsprojektes CERTCOST entstanden. Die Darlegung des Betreuers zum Anteil der eigenen wissenschaftlichen Leistung wurde beigefügt.

Stuttgart-Hohenheim, den 31. Januar 2012