



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

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

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

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

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

*No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.*

# Optimizing Inspection Strategies to Enforce Organic Farming Standards

## Optimierung der Kontrollstrategien zur Durchsetzung von Öko-Standards

Christian Lippert  
Universität Hohenheim, Stuttgart, Germany

Alexander Zorn  
Agroscope, Ettenhausen, Switzerland

Stephan Dabbert  
Universität Hohenheim, Stuttgart, Germany

### Abstract

*The organic market depends on an effective and efficient certification system. Control bodies or authorities are pivotal to this system. From a social point of view, our objective is to theoretically optimize inspection strategies. For this, sanctions and inspection frequencies have to be implemented in a way that the net social damage arising from farmers' non-compliance with an organic standard will be minimized. In scenarios that combine different kinds of social damages, fines and compliance cost distributions for an assumed set of farms we use Monte Carlo simulations to model farmers' non-compliance and resulting social damages. Depending on potential reputation losses and compliance cost variability among farms we identify different adequate control frequencies.*

### Key Words

*organic farming standard; enforcement; economics of crime; optimized control system*

### Zusammenfassung

*Der Markt für ökologische Produkte basiert auf einem wirksamen und effizienten Kontrollsystem. Kontrollstellen bzw. -behörden sind ein zentrales Element dieses Systems. Unser Ziel ist es, die Kontrollstrategie anhand eines theoretischen Modells zu optimieren. Dabei sollen Strafen und Kontrollhäufigkeiten so festgelegt werden, dass der volkswirtschaftliche Netto-Schaden, der sich aus der Verletzung eines Öko-Standards ergibt, minimiert wird. In Szenarien, die für eine Gruppe von Landwirten Verteilungen zu den betrieblichen Kosten der Standardeinhaltung, unter-*

*schiedliche volkswirtschaftliche Schäden und Strafen kombinieren, werden mit Hilfe von Monte-Carlo-Simulationen die Anzahl der jeweils resultierenden Standardverletzungen und die daraus folgenden volkswirtschaftlichen Schäden abgeschätzt. Unter Berücksichtigung möglicher Reputationsverluste sowie der Variabilität der Kosten der Standardeinhaltung unter den Öko-Landwirten werden entsprechend optimierte Kontrollhäufigkeiten abgeleitet.*

### Schlüsselwörter

*Öko-Landbau; Richtlinien; Kontrolle; ökonomischer Ansatz zur Erklärung von Kriminalität; Kontrollstrategie*

## 1 Introduction

An organic farming standard governs the organic farm production process by detailed rules. The adherence to the rules of an organic standard by a farm producer is inspected by an independent third party, the control body (CB) (DABBERT et al., 2012). A system of quality control and corresponding labeling is pivotal for the existence of a global organic food and beverage market, whose sales in 2013 were found to approach 72 billion US dollars (SAHOTA, 2015: 120).

Enforcing compliance with organic farming standards can be seen as a public good for organic producers and consumers. Our objective is to theoretically determine socially optimal inspection strategies to provide for this public good. From a social point of view the questions whether a state run agency or another third party should implement the necessary inspections and whether taxpayers or organic producers

should finance them are secondary and will not be treated in this article. In the European Union public authorities or private control bodies (both subsumed under CB in the following) need to perform at least one annual inspection per organic operator. In addition further inspections are implemented. These additional controls are often discussed in the context of the request to implement a risk based inspection system (EUROPEAN COURT OF AUDITORS, 2012). For every rule contained in an organic standard a CB trying to perform risk based farm inspections needs to ponder both the risk of non-compliance and the related possible social damages (BMELV, 2012).

There are recent studies that empirically and quantitatively investigate non-compliance with organic farming standards (LIPPERT et al., 2014; ZORN et al., 2013; GAMBELLI et al., 2014; ZANOLI et al., 2014). Based on data from CBs these papers attempt to find out which factors do significantly increase the probability of non-compliance. A multitude of hypotheses is investigated and in the different studies several significant effects are found; however, the only common element detected is that already observed non-compliance – either in the past or as different kind of non-compliance in the same year – seems to increase the likelihood of non-compliance. The approach of these papers – while novel with respect to using original data from CBs – implies some limitations due to the nature of the data used. The mentioned authors are not able to directly statistically explain the probability of detected non-compliance, because the term non-compliance is not legally clearly defined and thus cases of “non-compliance” were not adequately coded in the data bases of the investigated CBs; besides, data changes over time with one CB and is not comparable across CBs. Thus, in their analysis they investigate the probability of issued and reported sanctions or of different groups of issued sanctions as a proxy for actual detected non-compliance. A further problem that limits the direct applicability of these studies for implementing better control strategies with CBs is that some variables that are unobservable but nevertheless important are not taken into account. Thus it can be concluded, that a broader, more theoretically based approach would be needed to devise better control strategies.

This article theoretically analyses enforcement measures by CBs designed to reduce the occurrence of non-compliance with an organic standard in a broader view (for an overview of reported past non-compliances in Germany see ZORN et al., 2012). We pos-

tulate that – besides accounting for inspection costs, detection probabilities and deterring effects – CBs planning their inspections should continuously balance all relevant social costs including all possible societal damages linked to different kinds of non-compliance. In principle, we apply the established economics of crime approach (see below) to the problem of non-compliance in organic farming. Two types of social costs matter in this context: “the net harm caused by crime and the resources spent on preventing it” (COOTER and ULEN, 2008: 510). Efficient deterrence means to balance these two kinds of cost (COOTER and ULEN, 2008). In our case relevant social costs or social damages corresponding to *harm caused by crime* are the environmental and consumer damages due to defective organic production and income losses of the whole organic farming sector caused by non-compliance that remains undetected at farm level but later may lead to organic food scandals once the faulty produce is put on the market. Neglecting the costs of lawsuits as well as the costs of implementing and sustaining the legal system and the administrative costs of the organic certification system, considered as fixed cost here, *resources spent on prevention* in our case correspond to the costs of farm inspection visits.

The behavioral models developed by HIRSCHAUER (2004) and HIRSCHAUER and MUBHOFF (2007) refer to principal-agent theory to analyze food risks. Extending this approach, we focus on the decision problem of a third party next to sellers and buyers, an independent CB, which has to implement a cost-efficient control system. In contrast to current practice in the organic farming sector this independent CB is fully entitled to decide on how frequently different farm types are to be inspected. Relying on few qualitative assumptions mainly founded in the theory of economics of crime we set out to build an economic model to explain farmers’ non-compliance. This model is used to derive hypotheses on farmers’ behavior and number of non-complying farms. Next, different kinds of social damages linked to non-compliance with organic farming process standards are introduced and a social damage function relating these damages to the number of non-complying farms is built. Going from the general to the specific we finally make quantitative assumptions on the functional forms and parameter values of the model’s equations and inequalities in order to model the interplay of important factors that are likely to determine non-compliance in organic farming, all the more as the econometric studies quoted above, because of lacking data in this field,

did not deal with any inspection induced changes of compliance behavior or with any social cost of non-compliance. Hence, our quantitative decision model finally obtained is a rule-based model not to be seen as a direct representation of reality but helping to better analyze and perhaps improve the organic control system.

The structure of this paper is as follows. In section 2, the decision of an opportunistic and/or inadvertent farmer to comply with a certain process standard is modeled, based on the theory of economics of crime. In section 3, a more specific decision model for CBs is developed that is built upon the calculus model from section 2, and then used to optimize a CB's inspection frequency given the assumed inspection costs and the inspection frequency's impact on non-compliance and on the related social costs. In section 4, for selected functional relationships and parameter settings, optimum inspection strategies are discussed using a ceteris paribus analysis. Section 5 contains our main conclusions.

## 2 Theoretical Model Explaining Organic Farmers' Non-compliance

Following the *economics of crime approach*<sup>1</sup> 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 (see EHRLICH, 1974; EIDE et al., 1994; ANTONY and ENTORF, 2002), the long-term relationship between inspection frequency and incidence of non-compliance should be negative.

We assume that at least part of the organic farmers 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. The compliance cost may also contain 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 theoretical approach by ALMER and GOESCHL (2008: 6f.)<sup>2</sup>, 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 (see LIPPERT et al., 2014: 314ff.). If

$$B_{(NC_{it}=1)} = C_t(s_i, fc_i) - P_d(\cdot) P_s(SF_{t-1})(F + L(\cdot)) + \varepsilon_{it} > 0 \quad (1)$$

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

$P_d(\cdot)$  =  $P_d(s_i, fc_i, IF_{t-1}, IR_{t-1})$

$L(\cdot)$  =  $L(s_i, fc_i, d(fc_i))$

$t$  = time period (e.g., year)

$i$  = farm number ( $i = 1, \dots, n$ )

$B_{(NC_{it}=1)}$  = Net benefit of non-compliance

$NC$  = Non-compliance ( $NC_{it} = 1$  if farmer  $i$  does not comply in time period  $t$ ,  $NC_{it} = 0$  otherwise)

$C$  = Compliance cost saved when infringing upon the standard and which depends on-site  $s$  (location of the farm) and a vector  $fc$  containing farm and farmer characteristics like farm size and type (e.g., dairy farm or arable farm), farmer's experience and farmer's liquidity

$P_d$  = (Subjective) probability of being detected in the case of non-compliance during the respective time period depending on  $s$  and  $fc$  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)

$P_s$  = (Subjective) probability of being sanctioned when detected, which depends on  $SF$  = (perceived) sanction frequency in the case of detected non-compliance related to the kind of standard (its seriousness) that has to be observed

<sup>1</sup> For an overview on the *economics of crime* approach with special regard to compliance in agriculture, see HERZFELD and JONGENEEL, 2012: 251ff.

<sup>2</sup> The modified empirical part of the analysis by ALMER and GOESCHL (2008) has been also published in ALMER and GOESCHL (2010). However, this latter publication does not contain the theoretical model we are referring to here.

- $F$  = 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  $s$ ,  $fc$  as well as on the farmer specific discount rate  $d_i$
- $\varepsilon_{it}$  = Error term reflecting further individually different net benefit-determining factors, such as the “warm glow” discussed herein, as well as a random error.

Hence, we address an *incentive constraint*, which, in our case, is fulfilled when the net benefit of non-compliance  $B_{(NC_{it}=1)}$ , as defined in inequality (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, i.e. organic farmers’ utility derived from correctly farming organically is always greater than the respective reservation utility (for an application of different models of principal agency theory to food safety issues, see HIRSCHAUER, 2004).

Inequality (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: 622) – in our model (for a similar application in the context of food safety standard enforcement, see LIPPERT, 2002). Consequently, an indirect sanction resulting from additional market sanction-related losses  $L$  is added to the possible direct sanction (fine  $F$ ). In our model, the non-compliance related losses do not occur certainly and without any third-party inspection as in the case of the original idea of self-enforcing agreements (which implies experience qualities). Instead – as in organic farming immaterial credence qualities matter – these losses are to be borne only at a certain probability, which strongly depends on the CB’s detection efforts.

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 when a certain non-compliance is detected, as well as on the corresponding time span during which organic marketing will be prohibited. In the case in which a batch of cheese ready for sale 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.<sup>3</sup>

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 (1).

Again depending on the personality of the respective farmer, costs,  $C_i$ , may be completely compensated by the good feeling – a “warm glow” – linked to compliance with the organic standard. Consequently, a given group of farmers may consist of two subgroups: non-opportunistic farmers for whom  $NC_{it}$  is always

<sup>3</sup> Since  $L$  is a present value of future losses its amount does not only depend on the future (expected) income possibilities when selling organic produce but also on the rate at which these future (possibly lost) benefits are discounted. Ceteris paribus,  $L$  will decrease with an increasing discount rate (with a higher time preference) of the farmer. Further,  $L$  is also influenced by the (assumed) probability of being detected sometime in the future when not being detected in the present time period. For an intertemporal theoretical analysis on how compliance behavior is simultaneously affected by the producer’s discount rate and the detection probability see VETTER and KARANTININIS (2002: 273f.) and the similar approach in the context of forest certification by LIPPERT (2009: 145ff.). These analyses also explicitly account for the possibility that non-compliance may be detected at later time periods.

zero and opportunistic farmers who will continuously ponder their behavior according to inequality (1).

Let  $x$  be any farm specific factor that determines the magnitude of the net benefit,  $B_i$ , of a given type of non-compliance that when detected and punished, entails direct ( $F$ ) and/or indirect ( $L$ ) sanctions. Thus, it follows that as long as

$$\frac{\partial B_{(NC_{it}=1)}}{\partial x} = \frac{\partial B}{\partial x} > 0 \quad (2)$$

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

- (i) to a higher probability  $P(NC_{it} = 1)$  that a certain opportunistic farmer  $i$  does not comply with the corresponding standard and
- (ii) to a higher overall number of non-complying farmers ( $NCF$ ) as the net benefit  $B_{(NC_{it}=1)}$  in inequality (1) will become positive for more opportunistic farmers.

Because

$$\frac{\partial B}{\partial P_d} = -P_s(\cdot)(F + L(\cdot)) < 0 \quad (2a)$$

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 increasing the inspection frequency or the monetary value of sanctions.

Building on the microeconomic theory as treated in this section, in subsection 3.1, we 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. In subsection 3.2, we develop a simplified decision model that – using assumptions for parameters and social damage functions – allows for analyzing the interplay of these factors when designing inspection strategies.

### 3 Model for the Optimization of Inspection Strategies to Reduce Organic Farmers' Non-compliance

#### 3.1 General Model Structure

Our normative analysis is based on the idea that a CB 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, see BECKER, 1974; BECKER, 1976; PYLE, 1983; for an application to food safety performance standards, see LIPPERT, 2002).

In the following, we consider a group of  $n_k$  organic farmers who are identical with respect to site conditions  $s$  and some of the farm characteristics  $fc$ . 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 differing characteristics between the farms determine the differences in compliance behavior within the group.  $NCF_{kt} \leq n_k$  is the number of non-complying farmers in time period  $t$  within the group.

Notice that the inspections considered in our model are spot checks that verify whether a certain rule 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  $n_k$  farms 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 mineral nitrogen fertilizers, the banning of certain pesticides or the implementation of specific documentary requirements. Such a separated consideration of the rules is necessary because of the varied magnitude of the related damages. Damages resulting from an infringement of documentary requirements are likely to be small, whereas ecological and other (sectoral) social damages linked to the use of a forbidden pesticide can be very high.

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

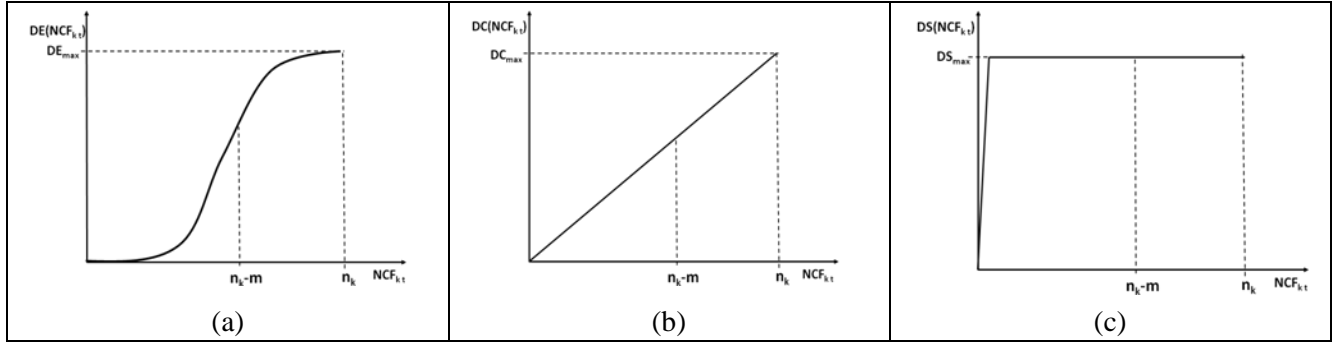
$DE(NCF_{kt}) =$  *Ecological damage* resulting from foregone positive externalities linked to compliance,

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

$DS(NCF_{kt}) =$  *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 rule considered. For the first category, it seems plausible to assume a cubic damage function



**Fig. 1. Examples for possible social damage functions**

$DE$  = 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;  $DE_{max}$  = maximum possible ecological damage;  $DC_{max}$  = maximum possible consumer damage and  $DS_{max}$  = maximum possible sectoral damage.

Source: authors

as the one displayed in Fig. 1a, which means *Ecological damage* ( $DE$ ) – for example, due to pesticide emissions – is characterized by increasing marginal damages until a certain number of non-complying farms is reached. From this point on marginal ecological damage ( $\partial DE(NCF_{kt})/\partial NCF_{kt}$ ) is still positive but declines until a maximum damage ( $DE_{max}$ ) is attained. 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.

*Consumer damage* ( $DC$ ) occurs either when a purchaser unwittingly consumes faulty food items. These products could come from undetected non-complying farms whose products do not have the characteristics paid for. In this case, the related marginal damage is difficult to assess as it may be different for each consumer. As it cannot be established whether a defective product will be consumed by somebody who values this fact more or less seriously, a constant marginal damage is assumed, leading to a linear damage function, as the one shown in Fig. 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 exceeds organic market prices, such an estimate would be a lower bound of the true social damage  $\partial DC(NCF_{kt})/\partial NCF_{kt}$ .

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*, e.g., in time period  $t+1$ .

In such cases, just one non-complying farm not duly excluded from organic business could result in a huge loss of consumer trust in the organic farming business. As consumer trust is an important prerequisite for obtaining premium prices in the organic sector (see 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 Fig. 1c: only a few, or even one, non-complying farmer may cause maximum possible sectoral damage.

Considering both, the mentioned social costs linked to non-compliance and the CB's costly inspection and sanction effort  $E_t$ , the objective is to optimize the number of non-complying farmers  $NCF_{kt}$ . Therefore, from the perspective of a CB, acting on behalf of the natural environment, consumers and the whole organic sector, the following net damage  $G$  has to be minimized by choosing an optimum inspection frequency  $IF_t$  (symbols used as introduced above):

$$\begin{aligned}
 G = & DE(NCF_{kt}) + DC(NCF_{kt}) \\
 & + DS_{t+1}([1 - P_d(IF_t, IR_t)]NCF_{kt}) \\
 & + E_t(IF_t, IR_t, SF_t) \\
 & - P_d(IF_t, IR_t)SF_t NCF_{kt} \text{ min!}
 \end{aligned} \tag{3}$$

with

$$NCF_{kt} = NCF_{kt} (P_d(IF_{t-1}, IR_{t-1}), P_s(SF_{t-1}), F) \quad (4)$$

where  $DS_{t+1}(\cdot)$  is the discounted future sectoral damage as defined above resulting from non-complying farms not detected  $((1-P_d) NCF_{kt})$  in time period  $t$ .

The dynamic problem is to minimize net damage  $G$  every year again balancing the time dependent variables contained in Equations (3) and (4). The dynamics result from the fact that a change of the CB's behavior in time period  $t-1$  (e.g., an increase in inspection frequency  $IF_{t-1}$ ) entails a change of the number of non-complying farms ( $NCF_{kt}$ ) in the next time period which in turn will make the CB adapt its inspection frequency  $IF_t$  again etc. This leads to (optimum) time paths for the variables *inspection frequency* and *number of non-complying farms*. Next, to facilitate the theoretical analysis we assume that within this dynamic system sooner or later a steady state will be reached, where, for all relevant variables, the optimized values  $v = v_{t+1} = v_t = v_{t-1}$ . In such a steady state an equilibrium detection probability and an equilibrium number of non-complying farmers is given in a way that neither the farmers nor the CB will adapt their behavior in the following time periods as long as there is not any exogenous change of variables or model parameters. By means of the simplified heuristic model below, we compare steady states brought about by the different model parameters like, e.g., the fine in case of detected non-compliance. In doing so, farmers' compliance cost  $C_i$  – which in reality may be time dependent especially for some crop production standards – are supposed to vary among farmers but to be time-invariant.

The damages  $DE$  and  $DC$  are directly related to the number of non-complying farms ( $NCF_k$ ) whereas  $DS$  depends on the number of *undetected* non-complying farms  $((1-P_d) NCF_k)$  as only the produce of these farms, once being marketed, results in social damages to the whole organic farming sector.

An increase in the inspection frequency may have two damage reducing effects: an *indirect* effect resulting from deterrence (less  $DE$ ,  $DC$  and  $DS$  because of fewer non-complying organic farmers) 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  $DS$ ).

Finally, a further aspect needs to be mentioned. Following the idea already put forward by JEREMY BENTHAM in 1823 (1907: 171, 175) that an offender's harm due to punishment should not exceed the dam-

age to be avoided, from an overall social point of view, this constraint should be observed:

$$\begin{aligned} & P_d(IF, IR) P_s(SF) [F + L_{MNC}] \\ & \leq \frac{\partial DE}{\partial NCF_k n_{MNC}} + \frac{\partial DC}{\partial NCF_k n_{MNC}} \\ & + (1 - P_d(IF, IR)) \frac{\partial DS}{\partial NCF_k n_{MNC}} \end{aligned} \quad (5)$$

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 (1)) should be less or equal to the related expected marginal damage caused to other members of the society (i.e. environmentally concerned citizens, consumers and the whole organic sector).

### 3.2 Simplified Decision Model

To demonstrate further implications for optimum inspection strategies, sensible parameter values assuring realistic orders of magnitude have been specified (see the parameters given below Figures 2 through 7).

For simplification we assume that in the analyzed steady state,  $P_d(IF) = IF$  such that  $\partial P_d / \partial IF = 1$ . A further simplification of assumptions affects both inspection rigor  $IR$  and sanction frequency when non-compliance is detected (in the following,  $P_s = SF = 1$ ). We thus assume these values to be given, they cannot be influenced.

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 Fig. 1c. 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 ecological 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  $DE(n_k) = DE_{max}$ . As mentioned, we assume a cubic damage function



(i.e., initially increasing, later decreasing marginal damage, see Fig. 1a). When assuming  $DE(0) = 0$ ,  $DE(n_k) = DE_{max}$  and  $\partial DE(0)/\partial NCF_k = \partial DE(n_k)/\partial NCF_k = 0$ , this function can be written as

$$DE(NCF_k) = 3 \frac{DE_{max}}{n_k^2} NCF_k^2 - 2 \frac{DE_{max}}{n_k^3} NCF_k^3. \quad (6)$$

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

A simple way to model a CB's inspection cost for a given inspection rigor,  $IR$ , is to assume

$$E(IF|IR) = E(IF) = c_v n_k IF \quad (7)$$

$$\Rightarrow \frac{\partial E(.)}{\partial IF} = c_v n_k$$

with  $c_v$  = cost per inspection visit.

Finally, the relationship between the equilibrium probability (i.e., the probability in the assumed steady state) of being detected when not complying 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 (1), an opportunistic farmer's compliance costs,  $C_i$ , and her expected overall losses,  $P_d (F + L_i)$ , when being detected as non-compliant determine whether she will comply with the standard or not (see corresponding inequality (1b), below).

In the following, the variables  $L_i$  and  $C_i$  are assumed to be normally distributed ( $N(\mu_L, \sigma_L^2)$ ;  $N(\mu_C, \sigma_C^2)$  and independent). Especially, in case of compliance costs in reality also a positively skewed distribution (i.e., few farms with particularly high compliance costs) could be relevant. Note, 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. In every model simulation below, using the assumed normal distributions, random values

for  $C_i$  and  $L_i$  are drawn. Then, every risk-neutral<sup>4</sup> opportunistic farmer  $i$  ( $i = 1, \dots, n_k - m$ ) checks for the given fine,  $F$ , at every probability  $P_d$  between 0 and 1 whether

$$B_{(NC_i=1)} = C_i - P_d (F + L_i) > 0. \quad (1b)$$

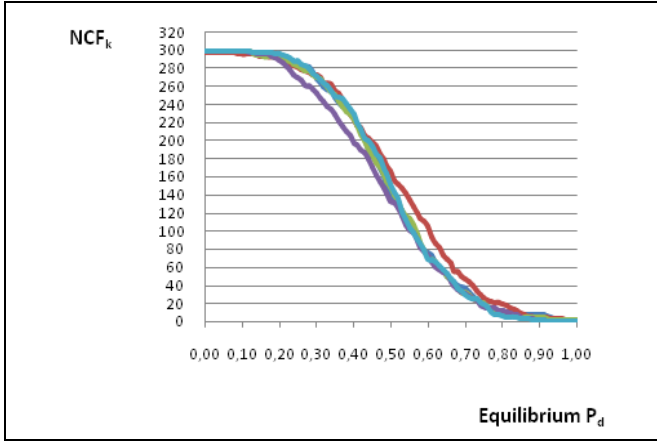
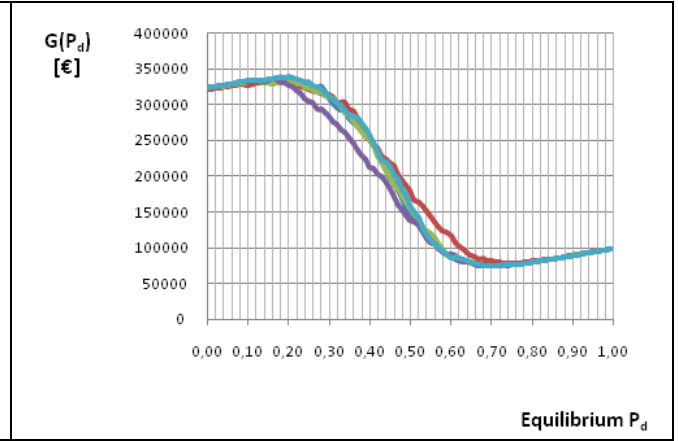
Those farmers for whom the net benefit  $B_{(NC_i=1)}$  according to inequality (1b) is positive will be non-compliers ( $NC_i = 1$ ). Summing up all non-compliers at different probabilities,  $P_d$ , yields a curve,  $NCF_k(P_d)$ , that is used to calculate the respective net damage,  $G(P_d)$ , as defined in Equation (3).

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,  $\mu_C = 800$  €; the average loss  $L$  is  $\mu_L = 1,600$  €. Initially, the standard deviations are set to  $\sigma_L = 160$  € and  $\sigma_C = 250$  €. A cubic damage function corresponding to Eq. (6) and Fig. 1a is used.

## 4 Model Simulations to Identify Optimum Inspection Strategies under Different Scenarios

In this section we present one reference scenario and five additional scenarios in which important model parameters have been modified when compared to the reference scenario (for a complete overview on the model parameters used in the different scenarios see the summarizing representations below Figures 2 through 7). After the *reference scenario* without any fine and with zero sectoral damage we introduce a fine of 2,400 € in *scenario I* (this fine is then retained in scenarios I through V). In addition, in *scenario II* the standard deviation of the compliance cost is increased; in *scenario III* it is reduced when compared to the reference situation. In *scenario IV* we keep the parameter values assumed in scenario I except the average compliance cost that are supposed to be higher now. *Scenario V* – again based on the parameter values of scenario I – illustrates the effects of an important

<sup>4</sup> Risk-averse behavior could be modeled by subtracting a risk premium  $r_i(P_d, F+L_i)$  from the left-hand side of inequality (1b). However, this addition would strongly complicate the analysis as it implies assigning individual utility functions to the different farmers.

**Fig. 2a. Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$** **Fig. 2b. Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$** 

Model parameters for the *reference scenario*:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

$DS_{max} = 0$  €;  $\partial DS / \partial NCF_k = 0$  €;  $\mu_C = 800$  €;  $\sigma_C = 250$  €;  $F = 0$  €

Source: authors

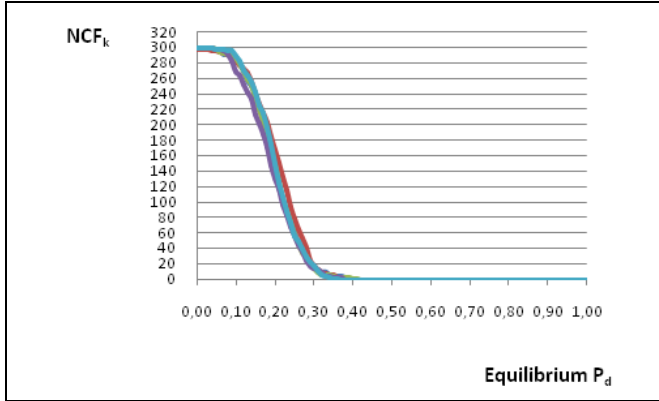
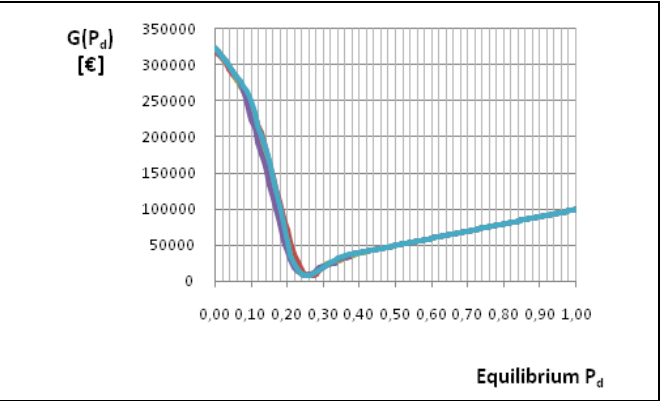
sectoral damage,  $DS$ , already occurring in case of only few non-complying farms. For every scenario, five Monte Carlo simulations are performed. In each simulation,  $n_k - m$  combinations of  $C_i$  and  $L_i$  are drawn from the assumed distributions. Then, for 100 probabilities between 0 and 1, each farm  $i$  is assigned its compliance status according to inequality (1b). Finally, for every simulation, 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.

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 simulations of the reference scenario are shown in Fig. 2a and 2b. Depending on the simulation, the optimum inspection frequency corresponds to approximately 74%, and the corresponding minimized net damage is between 75,000 and 80,000 €. In the optimum, between 18 and 30 non-complying farms would be accepted by the CB. However, if, in addition, restriction (5) was to be observed, the inspection frequency should be lowered (to approximately 57% in simulation 1) until the damage,  $\partial DE / \partial NCF_k$ , of the marginal non-complying farm ( $NCF_k = 95$  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,  $DE$ , 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 Fig. 3a and 3b. Now, the optimum inspection frequency is approximately 25%, and the corresponding minimized net damage is approximately 9,000 €. In the new optimum, more non-complying farms ( $\approx 60$  except for simulation 2) would exist. Nevertheless, the net damage 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), the inspection frequency could be further reduced, but only slightly (to approximately 22% in simulation 1).

While maintaining all other parameters from scenario I in the following two scenarios, we vary the standard deviation of compliance cost  $\sigma_C$ . Fig. 4 (*scenario II*, high  $\sigma_C$ ) and 5 (*scenario III*, low  $\sigma_C$ ) reflect the resulting effects on the number of non-complying farms and on net damage. Obviously, when opportunistic farmers are rather homogeneous regarding their compliance costs (i.e., low  $\sigma_C$ ) 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.

Especially with respect to organic crop farming, compliance costs for the fulfillment of certain rules

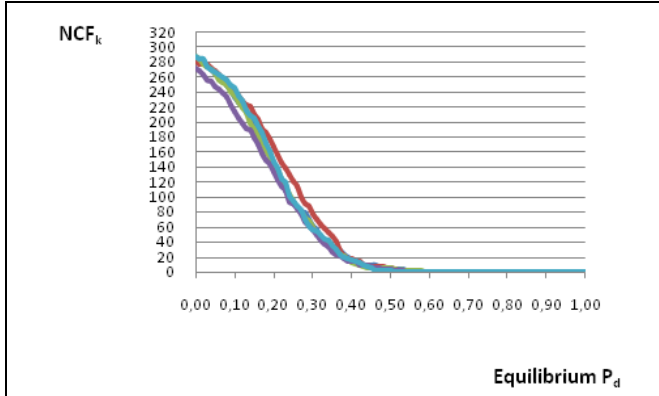
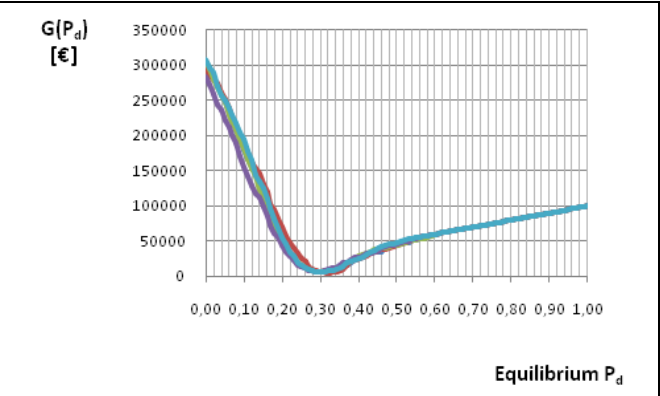
**Fig. 3a.** Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$ **Fig. 3b.** Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$ 

Model parameters for *scenario I*:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

$DS_{max} = 0$  €;  $\partial DS / \partial NCF_k = 0$  €;  $\mu_C = 800$  €;  $\sigma_C = 250$  €;  $F = 2,400$  €

Source: authors

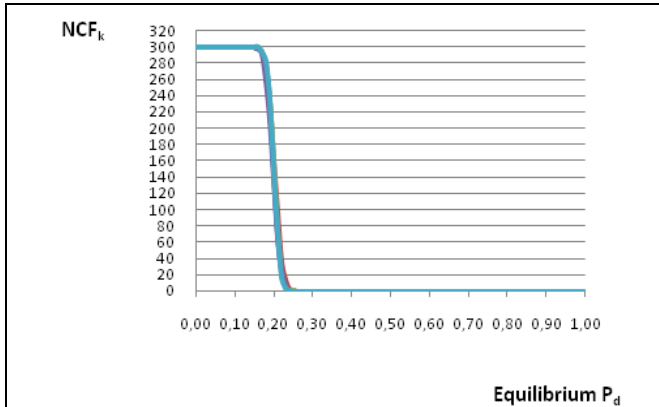
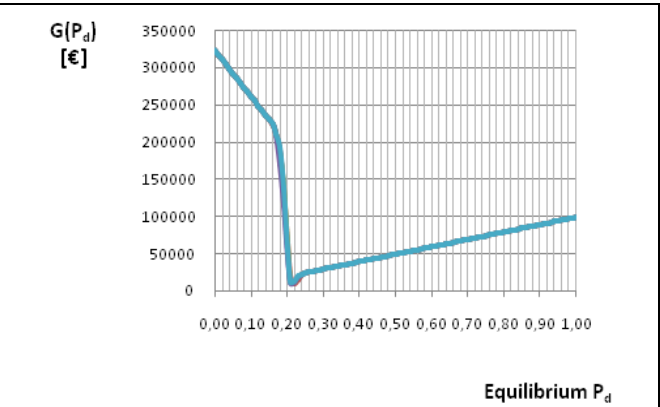
**Fig. 4a.** Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$ **Fig. 4b.** Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$ 

Model parameters for *scenario II*:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

$DS_{max} = 0$  €;  $\partial DS / \partial NCF_k = 0$  €;  $\mu_C = 800$  €;  $\sigma_C = 500$  €;  $F = 2,400$  €

Source: authors

**Fig. 5a.** Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$ **Fig. 5b.** Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$ 

Model parameters for *scenario III*:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

$DS_{max} = 0$  €;  $\partial DS / \partial NCF_k = 0$  €;  $\mu_C = 800$  €;  $\sigma_C = 50$  €;  $F = 2,400$  €

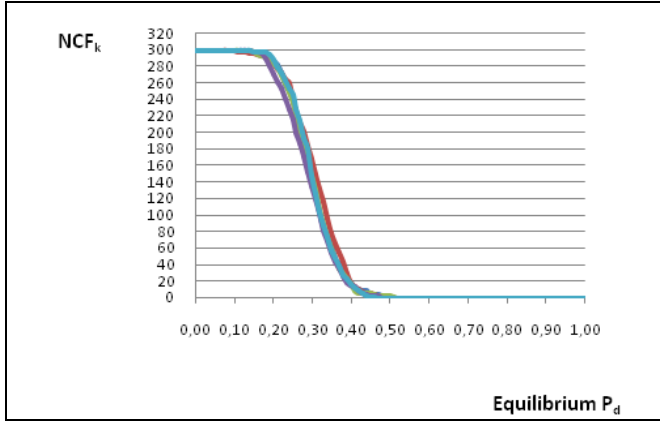
Source: authors

may strongly vary between regions. For instance, due to humid weather conditions during the growing season, the opportunity costs for renouncing certain banned pesticides could be greater at a certain place. In **scenario IV** (see Fig. 6), we maintain all parameters assumed in scenario I except the average compliance cost,  $\mu_C$ , for which we simulated an increase of 50%. As a consequence, in the model, the CB's optimum inspection frequency increases from approximately 25% to roughly 34%. At the same time, minimized net damage, as defined by Eq. (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-

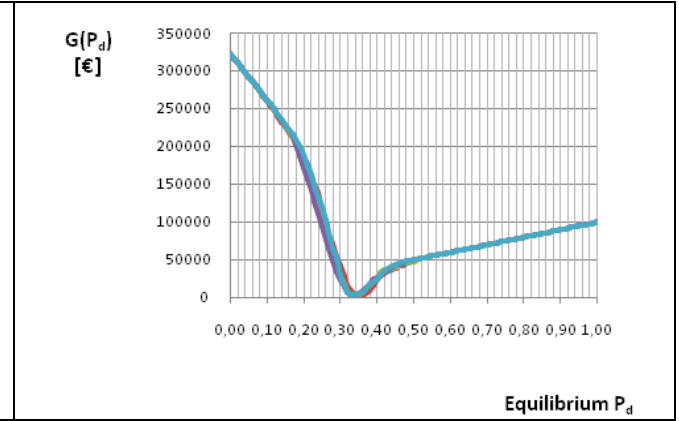
complying farmers increases from approximately 60 to 77.

Finally, in **scenario V** (see Fig. 7), we analyzed the effects of an important possible sectoral damage,  $DS$ , on optimized inspection frequencies and overall damage. 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 € and using a damage function such as the one displayed in Fig. 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 para-

**Fig. 6a.** Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$



**Fig. 6b.** Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$



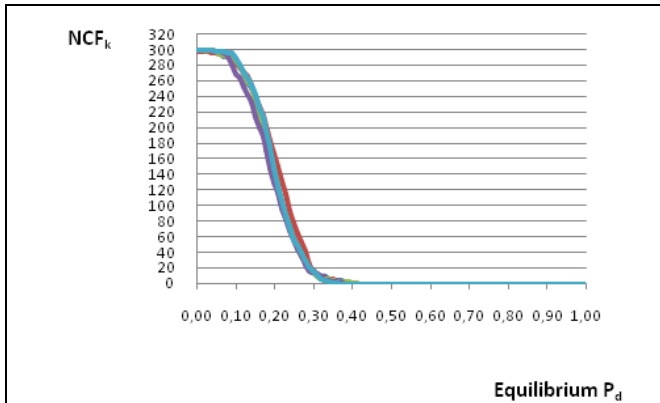
Model parameters for **scenario IV**:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

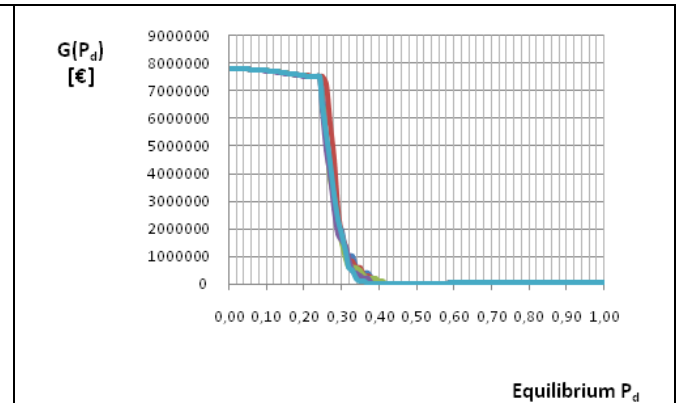
$DS_{max} = 0$  €;  $\partial DS / \partial NCF_k = 0$  €;  $\mu_C = 1,200$  €;  $\sigma_C = 250$  €;  $F = 2,400$  €

Source: authors

**Fig. 7a.** Number of non-complying farms  $NCF_k$  depending on detection probability  $P_d$



**Fig. 7b.** Net damage  $G$  (Eq. (3)) depending on detection probability  $P_d$



Model parameters for **scenario V**:

$P_d(IF) = IF$ ;  $SF = 1$ ;  $n_k = 500$ ;  $m = 200$ ;  $DE_{max} = 500,000$  €;  $c_v = 200$  €;  $\mu_L = 1,600$  €;  $\sigma_L = 160$  €;

$DS_{max} = 7,500,000$  €;  $\partial DS / \partial NCF_k = 150,000$  €;  $\mu_C = 800$  €;  $\sigma_C = 250$  €;  $F = 2,400$  €

Source: authors

meters are the same as in scenario I. 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 simulation, 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 damages. 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.

In principle, similar model analyses could be used by CBs to 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 Discussion

Our theoretical considerations and model analyses have shown that CBs planning efficient inspection strategies, should carefully ponder on the following factors: possible social damages from standard infringements, costs of inspection measures and compliance costs dependent on the farmers' abilities to change their behavior. 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, spot checks or tests, if conducted at all, should be conducted rarely).

Due to differences in compliance costs and losses resulting from sanctions different types of farms may demonstrate different compliance behaviors for the same rules. Thus, inspection frequencies should be targeted to farm types in such a way that a CB 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 CB is interested in directly avoiding sectoral damages (see  $DS_{t+1}$  in Eq. (3)).

Separating farms into relatively homogenous groups when designing inspection strategies means

that the effects of different control strategies on farmers' compliance behavior are easier to assess as all farmers react similarly (see section 4).

Inequality (1) in section 1 also illustrates that opportunistic farmers' expectations are based on previous experiences. It is thus suggesting that these farmers will adapt their compliance behaviors according to perceived past inspection and sanction frequencies. Consequently, a CB should adapt its inspection strategy continuously. This could be done using regularly up-dated discrete choice models that explain the determinants of actual non-compliance probabilities. Furthermore, CBs 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  $\partial NCF_k / \partial IF_{t-1}$ ).

By including a non-compliance dependent social cost function the model developed in this article extends the model elaborated in the theoretical part of LIPPERT et al. (2014), that merely addresses the determinants of farmers' compliance behavior as expressed by inequality (1). In this earlier work inequality (1) was used to systematically derive hypotheses for the incidence of non-compliance. In contrast, the extended model above should be seen as an attempt to structure a CB's problem of optimizing its inspections. We are well aware that it is based on several simplifying assumptions like risk neutrality of opportunistic organic farmers or the assumption that actual control frequencies are equivalent to perceived control frequencies. However, the model can still be helpful when abandoning one of these assumptions as it then illustrates the *ceteris paribus* effects of the corresponding previously neglected factor. For instance, allowing for farmers being risk averse (i.e., subtracting farm individual risk premia  $r_i$  from the left-hand side of inequalities (1b), see also footnote 4) leads to a *ceteris paribus* increase of the number of farmers for whom the benefit of non-compliance in equality (1b) is negative; consequently the  $NCF_k$ -curves in the model analyses and the related optimum inspection frequencies in the figures in section 4 would be shifted leftwards. Further, if – due to bounded rationality – farmers were supposed *not* being aware of sanctions or detection probabilities the number of non-complying farms  $NCF_k$  would be independent of these factors (thus, Equation (4) being irrelevant) but still the optimization problem outlined by means of Equation (3) would be relevant (in this case with a constant given number  $NCF_k$ ).



Finally, some caveats need to be mentioned. As illustrated in section 4, the implementation or increase of fines can facilitate standard enforcement and reduce corresponding damages. However, in practice, further transaction costs for related law suits and administration must be also 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 section 2. That is, assuming a certain probability of being sentenced innocently, conventional farmers may refrain from converting to organic farming.

Also we need to mention that the simulation model is still an abstraction from reality with respect to the legal situation within the organic sector. The idea, that a proactive CB should balance all relevant social costs when independently choosing its inspection frequencies, so far does not correspond to common inspection practices. One should be aware that the legislation would have to be changed if corresponding inspection strategies are to be implemented. Currently, also fines are not part of the sanctions a CB can impose. The current legal framework does not allow less than one inspection per operator and year – but this could be changed in the future. Also in principle the approach presented applies to the additional controls beyond the annual control.

Our model incorporates the concept of self-enforcing agreements (see section 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 who usually 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.

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.

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 (see 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 (see the literature quoted in HERZFELD and JONGENEEL, 2012: 255). In this context, a rule that does not make sense for the farmers is less likely to be strictly observed.

## References

- ALMER, C. and T. GOESCHL (2008): Environmental Crime and Punishment: A Dynamic Panel Data Analysis. Working paper presented at the PGPPE workshop on Environmental economics, 16-18 June 2008, Montpellier.
- (2010): Environmental Crime and Punishment: Empirical Evidence from the German Penal Code. In: *Land Economics* 86 (4): 707-726.
- AMODU, T. (2008): The determinants of compliance with laws and regulations with special reference to health and safety. A literature review. Prepared by the London School of Economics and Political Science for the Health and Safety Executive 2008. RR638. Published by the Health and Safety Executive. URL: <http://www.hse.gov.uk/research/rrpdf/rr638.pdf>.
- ANTONY, J. and H. ENTORF (2002): Zur Gültigkeit der Abschreckung im Sinne der ökonomischen Theorie der Kriminalität: Grundzüge einer Meta-Studie. Discussion Papers in Economics, No. 116 (June 2002). Arbeitspapiere des Instituts für Volkswirtschaftslehre, Technische Universität Darmstadt.
- BECKER, G.S. (1974): Crime and Punishment: An Economic Approach. In: Becker, G.S. and W.M. Landes (eds.): *Essays in the Economics of Crime and Punishment*. Columbia University Press, New York: 1-54.
- (1976): *The Economic Approach to Human Behavior*. The University of Chicago Press, Chicago and London.
- BENTHAM, J. (1907): *An Introduction to the Principles of Morals and Legislation*. Clarendon Press, Oxford.
- BMELV (Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz) (2012): *Verordnung über die Zulassung von Kontrollstellen nach dem Öko-Landbaugesetz*. BGBl Teil I Nr. 20. Bundesanzeiger Verlag, Köln.
- COOTER, R. and T. ULEN (2008): *Law & Economics*. Fifth Edition. Pearson Education, Boston.
- DABBERT, S., C. ABAY, S.R. BELLIERE, M. BOYACI, A. COMPAGNONI, I. FÖRSTER, D. GAMBELLI, U. HAMM, M. HARTMANN, B. HUBER, M. JANSSEN, L.M. JESPERSEN, C. LIPPERT, H. MOSCHITZ, L. PALUAN, L. PERIS, B. MIRAN, F. MEINSHAUSEN, S. PADEL, A. PULGA, E. RÜEGG, F. SOLFANELLI, M. STOLZE, Ö. KARAHAN



- UYSAL, J. VINE, R. ZANOLI and A. ZORN (2012): Economic analysis of certification systems in organic food and farming. Synthesis report of results from CERTCOST. CERTCOST, Universität Hohenheim, Stuttgart.
- EHRlich, I. (1974): Participation in Illegitimate Activities: An Economic Analysis. In: Becker, G.S. and W.M. Landes (eds.): *Essays in the Economics of Crime and Punishment*. Columbia University Press, New York: 68-134.
- EIDE, E. in cooperation with J. AASNESS and T. SKJERPEN (1994): *Economics of Crime. Deterrence and the Rational Offender*. North Holland, Amsterdam, Lausanne, New York, Oxford, Shannon, Tokyo.
- EUROPEAN COURT OF AUDITORS (2012): *Audit of the control system governing the production, processing, distribution and imports of organic products*. European Court of Auditors, Luxembourg.
- GAMBELLI, D., F. SOLFANELLI, R. ZANOLI, A. ZORN, C. LIPPERT and S. DABBERT (2014): Non-compliance in organic farming: A cross-country comparison of Italy and Germany. In: *Food Policy* 49: 449-458.
- GIANNAKAS, K. (2002): Information asymmetries and consumption decisions in organic food product markets. In: *Canadian Journal of Agricultural Economics* 50 (1): 35-50.
- HERZFELD, T. and R. JONGENEEL (2012): Why do farmers behave as they do? Understanding compliance with rural, agricultural, and food attribute standards. In: *Land Use Policy* 29 (1): 250-260.
- HIRSCHAUER, N. (2004): A model-based approach to moral hazard in food chains. What contribution do principal-agent-models make to the understanding of food risks induced by opportunistic behaviour? In: *Agrarwirtschaft* 53 (5): 192-205.
- HIRSCHAUER, N. and O. MUBHOFF (2007): A game-theoretic approach to behavioral food risks: The case of grain producers. In: *Food Policy* 32 (2): 246-265.
- JANSSEN, M. and U. HAMM (2011): Consumer perception of different organic certification schemes in five European countries. In: *Organic Agriculture* 1 (1): 31-43.
- KLEIN, B. and K. LEFFLER (1981): The Role of Market Forces in Assuring Contractual Performance. In: *Journal of Political Economy* 89 (4): 615-641.
- LIPPERT, C. (2002): Zur Ökonomik der Kontrollmaßnahmen bei Lebensmitteln und Futtermitteln. In: *Agrarwirtschaft* 51 (3): 142-155.
- (2009): Fraud and Free Riding in Tropical Forests - On the Potential for Certification to Enforce Sustainable Resource Use Indirectly. In: *Agrarwirtschaft* 58 (3): 144-154.
- LIPPERT, C., A. ZORN and S. DABBERT (2014): Econometric Analysis of Non-compliance with Organic Farming Standards in Switzerland. In: *Agricultural Economics* 45 (3): 313-325.
- PYLE, D.J. (1983): *The Economics of Crime and Law Enforcement*. Palgrave Macmillan, New York.
- SAHOTA, A. (2015): The Global Market for Organic Food & Drink. In: Willer, H. and J. Lenoud (eds.): *The World of Organic Agriculture. Statistics and Emerging Trends* 2015. FiBL-IFOAM Report. Publication by Research Institute of Organic Agriculture (FiBL), Frick (Switzerland), and International Federation of Organic Agriculture Movements (IFOAM) – Organics International, Bonn, Germany.
- STIGLER, J.G. (1970): The Optimum Enforcement of Laws. In: *Journal of Political Economy* 78 (3): 526-536.
- VETTER, H. and K. KARANTININIS (2002): Moral hazard, vertical integration, and public monitoring in credence goods. In: *European Review of Agricultural Economics* 29 (2): 271-279.
- ZANOLI, R., D. GAMBELLI, F. SOLFANELLI and S. PADEL (2014): Assessing the risk of non-compliance in UK organic agriculture: an econometric analysis. In: *British Food Journal* 116 (8): 1369-1382.
- 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. In: *Food Control* 25 (2): 525-532.
- (2013): An analysis of the risks of non-compliance with the European organic standard: A categorical analysis of farm data from a German control body. In: *Food Control* 30 (2): 692-699.

## 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 Zanolì. All remaining errors and mistakes are ours.

Contact Autor:

**PROF. DR. CHRISTIAN LIPPERT**

Institut für Landwirtschaftliche Betriebslehre (410),  
Fachgebiet Produktionstheorie und Ressourcenökonomik  
im Agrarbereich (410a), Universität Hohenheim  
Schloss Osthof-Süd, 70599 Stuttgart, Germany  
e-mail: [Christian.Lippert@uni-hohenheim.de](mailto:Christian.Lippert@uni-hohenheim.de)