A game-theoretic approach to behavioral food risks: the case of grain producers
(revised personal version)

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Abstract

Food risks may be caused by malpractice of suppliers who exploit the fact that their production processes and resulting product properties cannot be directly observed by buyers. The probability of malpractice increases with the profits that can be earned through opportunistic behavior. In this paper, we develop a moral hazard model for the empirical analyses of behavioral risks. It accounts for the essential fact that incomplete inspection and tracing increase the profitability of rule-breaking behavior, and that monitoring, tracing and sanctioning are costly. Using the model, we first demonstrate how to design efficient contracts in various situations. In a case study, we then analyze farmers' incentives with regard to the minimum waiting period after fungicide use. Data are gathered in interviews with three large-scale German farmers and a grain dealer. We find that, while their perception of parameters varies widely, high temptations for rule-breaking arise in some cases. We conclude that empirical moral hazard analyses have significant potential to shed light on behavioral risks.

Keywords: Behavioral food risks; Contract design; Moral hazard; Sample inspection, Traceability

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Introduction to behavioral food risk

Incentive problems related to information asymmetries have been studied extensively in different contexts: labor contracting (e.g. Epstein, 1991), insurance (e.g. Arnott and Stiglitz, 1991), delegation of decision making (e.g. Milgrom and Roberts, 1992), purchasing products under quality uncertainty (e.g. Akerlof, 1970; Stiglitz, 1987), and others.

One branch of literature concerned with the impact of imperfect information in food chains analyzes coordination problems and the evolution of industry structures in the agrifood sector. An overview of this branch of research - commonly associated with the label "organizational or new institutional economics" - is e.g. given by Ménard and Klein (2004). Organizational economists consider institutional change (e.g. increasing vertical integration) as a result of choices made by economic actors who economize on transaction costs (cf. Williamson, 1988; Ménard and Valceschini, 2005). However, within any existing institutional environment conflicting interests persist, and economic actors may want to analyze, from an operational-level perspective (cf. Ostrom, 2005), how they should design contracts and controls in their respective (trans)action situation.

Transactions under quality uncertainty are carried out on all levels of the food chains. Processing decisions made by suppliers affect the probability distributions of the product properties which are relevant for buyers. Buyers (be they food business operators on various chain levels or consumers) cannot contract contingent on actual actions because they cannot directly observe them (asymmetric information). Moreover, they cannot directly observe the product quality either. Price spreads for different quality categories as well as high costs of compliance with mandatory regulations may be reasons why suppliers are tempted to exploit such information asymmetries. Taking the buyer's point of view, the fact of asymmetric information is often described with the term credence quality. Credence qualities involve "simple" quality risks (i.e. the risk of being deceived with regard to a product's quality category) as well as "serious" health risks (i.e. the risk of processing or consuming substances which are harmful).

While being tantamount to technological practices and while leading to downstream diseconomies and unacceptable physical outcomes such as consumers' exposure to increased residue levels, the threat of opportunistic malpractice has been labeled moral hazard, emphasizing both the underlying cause of risk and the direction of potential countermeasures. Numerous food chain transactions might exist where non-compliance with norms and contractual agreements on the part of suppliers is more profitable than compliance. This is the reason why preventive measures aimed at eliminating misdirected incentives are an important field of action for the respective downstream food business operator as well as for public authorities which try to reduce food risks on behalf of consumers.

Formal moral hazard models (also known as principal agent or PA-models) have the general capacity to represent incentive problems. Regarding behavioral food risks the context is that of a buyer (principal) and a supplier (agent) of a raw material or (semi-) processed product with uncertain quality. The less well informed principal and his better informed agent have conflicting interests. While both maximize their respective objective function, the principal has the power to design an incentive-compatible contract that takes account of the agent's expected actions. Such contracts work independent of the moral attitudes of economic agents because they eliminate economic temptations to infringe rules and thus replace the need for *character trust* by *situational trust* (cf. Noorderhaven, 1996).

The general PA-perspective has been applied (implicitly or explicitly) to a vast variety of incentive problems in food chains - with differing emphasis on the impact of major aspects such as risk attitudes, production risk, suppliers' heterogeneity, output observability etc. Examples are Swinbank (1993) who focuses on the role of government in the face of imperfect information and market failure, or Weiss (1995) who considers the impact of information issues on both suppliers and buyers in the market for food safety. More recently, Olesen (2003), e.g., analyzes contract production of peas with heterogeneous growers in a tournament system. Dubois and Vukina (2004) look at the moral hazard costs associated with growers' risk aversion in livestock production contracts. Hueth and Melkonyan (2004) consider the effects of supplier heterogeneity in fruit/vegetable and livestock production contracts. Ligon (2004) suggests a procedure to design efficient contracts that takes account of stochastic production functions (estimated from experimental agronomic data) and of suppliers' risk aversion. A few authors consider partial inspection or multiple agents (c.f. e.g. Demski and Sappington, 1984; Fox and Hennessy, 1999; Starbird, 2005). Many other approaches exist which are tailored to specific situations and assumptions and which either provide theoretical insights into the structure of incentive problem in food chains or explanations for observed contracts. While providing information for specific constellations, their data requirements are quite demanding and usually include the estimation of actors' preferences as well as of stochastic production functions.

Adopting a more application-oriented approach to behavioral food risks, one needs to reconstruct systematically the empirical incentives in force on all chain levels. This facilitates the identification of critical (offence-prone) production activities according to the rationale that offences are most imminent if their technological viability coincides with a high level of economic temptation to break the rules. That is, interested parties first need to *assess behavioral food risks* (positive analysis) in order to identify those activities and places in food chains where deviance becomes a viable proposition to suppliers due to the fact that it is (highly) profitable. They then need to *manage behavioral food risks* (normative analysis) by trying to design efficient incentive-compatible contracts.

To the best of our knowledge formal models are lacking which represent operational and decision-oriented management tools in that they can be used and adopted by interested parties for a comprehensive empirical analysis of the real-life incentive situations arising on various food chain levels. The structure and data requirements of models that are suited for this purpose must be simple enough to be met by the empirical data that can be obtained at reasonable costs. This prevents, e.g., the use of highly sophisticated continuous models that rely on stochastic production and risk utility functions. Nonetheless, meaningful models must generate useful information and give at the least evidence about the magnitude of (misdirected) incentives. For this purpose, we need to consider *all* relevant factors in the transaction context that determine the incentives in force. Especially the knowledge gap regarding the impact of partial monitoring and incomplete tracing needs to be closed. That is, the crucial fact that quality can usually only be observed through random inspections, and the fact that product irregularities cannot always be traced need to be incorporated jointly into the model. Furthermore, with regard to normative conclusions regarding the design of cost-effective countermeasures, the costs of monitoring, sanctioning and setting up traceability systems need to be considered.

In this article, we aim at contributing to practical decision support (both for buyers faced with credence qualities and for public authorities acting on behalf of consumers) by developing a behavioral food risk model which can be used as a basis for systematic analyses of moral hazard problems in various food production contexts. We use the model in a theoretical analysis in order to examine how efficient incentive-compatible contracts need to be designed in different settings; i.e. we show how to determine the optimal value of those variables which are under the control of the principal in different time perspectives. We then briefly discuss the long-term decision problems related to structural change and system innovation in food chains.

Last but not least, we aim at demonstrating the practical use of the food risk model by applying it to a case study which tentatively investigates the incentive situations of grain farmers[1] regarding compliance with the minimum waiting period after fungicide use. The relevant data are gathered by interviewing three large-scale German grain farmers as well as their grain dealer. The case study shows that a realistic model which tries to reconstruct human behavior needs to incorporate the relevant factors *as perceived by the decision-makers*: one farmer, e.g., perceives high economic temptations to breach the waiting period, the two others don't because they expect very high sanctions in case of detection. While the grain dealer is convinced that high economic temptations for rule-breaking arise, he does not search for countermeasures. He states to rely on character trust instead. Interpreting the results it should be recognized that using a limited data set from a case study only provides preliminary hints about the regularities of the decision environment of German grain farmers at large. The case study does provide, however, information about the incentive situation as perceived by these randomly selected decision-makers. It is thus an informative and realistic model which sheds light on their incentive situation.

[1] For a comparable study concerning itself with the analysis of misdirected incentives in the poultry industry, see Zwoll and Hirschauer (2006).

The starting point: a standard moral hazard model

We resort to a general *discrete* PA-model as a starting point (cf. e.g. Grossmann and Hart, 1983; Kreps, 1990; Rasmusen, 1994). This standard discrete model reflects the following situation: a risk-averse agent has opportunity costs (reservation utility) μ for accepting a contract (for "participating"). If he participates, he has the choice between discrete actions a_n ($n = 1,2,\dots,N$) and corresponding deterministic efforts $k_n < k_{n+1}$. In a stochastic environment, these actions result – with probabilities π_{nm} – in discrete outputs $y_m < y_{m+1}$ ($m = 1,2,\dots,M$). For these outputs the principal defines output-dependent remunerations $w_m < w_{m+1}$. The agent's utility depends on his remuneration and effort ($u(w_m) - k_n$), where $u(w_m)$ represents a von Neumann-Morgenstern utility function.

The common structure of incentive problems caused by information asymmetries, opposed interests and stochastic environments is illustrated by this fairly general problem formulation. While the meaning of model parameters varies with investigated contexts, PA-models have the capacity to provide valuable conceptual insights into the structure of real-life incentive problems, including transactions where buyers (principals) purchase food products under quality uncertainty from better informed suppliers (agents).

However, empirical estimations of parameters such as prices, frequency and costs of control, traceability, level of sanctions etc. are needed to go beyond conceptual insights and provide intelligence for specific food chain activities and transactions. That is, if the model is to facilitate informed choices and practical conclusions, its data requirements must be met by the available empirical data from the chain activity under investigation. In this context it needs to be recognized that in many empirical situations expert opinion may be the main source of information for quantifying model parameters.

Consequently we will reduce the general discrete model to a "leaner" model which is able to account for the limited availability of data and which facilitates an empirical analysis with reasonable efforts and costs (cf. Hirschauer, 2004). First of all, the leaner model is "binary" in perspective ($N = M = 2$) and solely differentiates between two actions (a_1: straight non-compliance; a_2: straight compliance) and two outcomes (y_1: undesired quality; y_2: desired quality). Using the binary perspective and assuming that the principal is risk-neutral, his design problem can be stated as follows:

Step 1: determine the minimum wage costs $w_{min}(a_n)$ for both possible actions a_1 and a_2

$$\underset{w}{Min} \sum_{m=1}^{M} \pi_{nm} w_m = w_{min}(a_n) \tag{1}$$

$$s.t. \ \sum_{m=1}^{M} \pi_{nm} u(w_m) - k_n \geq \mu \tag{2}$$

$$\sum_{m=1}^{M} \pi_{nm} u(w_m) - k_n \geq \sum_{m=1}^{M} \pi_{n'm} u(w_m) - k_{n'} \quad n' = 1, 2 \tag{3}$$

Step 2: determine the maximum payoff over both possible actions a_1 and a_2

$$\underset{a_n}{Max}\left(\sum_{m=1}^{M}\pi_{nm}y_m - w_{min}(a_n)\right) \tag{4}$$

In PA-terminology, (2) is called the “participation constraint” and (3) the “incentive compatibility constraint”.

A moral hazard model for behavioral food risks

While being simple with regard to the modeling of the actions of suppliers and resulting outcomes, the binary model (1) to (4) does not yet include the two essential food risk characteristics which are common in most food transactions and which buyers need to take account of when purchasing food products under quality uncertainty: (i) the fact that quality can usually only be observed through random inspections (cf. incomplete observability of the output; cf. Holmström, 1979), and (ii) the fact that, even if a product irregularity is detected, it cannot always be traced to its origin.

Prohibitively high costs of complete inspection (e.g. because products are destroyed by tests) force the principal to resort to random controls. Control intensities $s < 100$ % result in incomplete information about the relevant output (product quality). If there are no further problems such as measurement errors, and if no commingling occurs before products are tested, the control intensity s represents the probability that an existing product irregularity is detected. However, in multiple agent settings (i.e. with many suppliers) the control intensity represents the probability that the originator of a product irregularity is detected if and only if we observe a quality signal which is unambiguously attached to the agent ($z = 1$). If the product quality is e.g. monitored at a downstream control point there may be only a probability $z < 100$ % that a single supplier is traced as the originator of a product irregularity. With regard to the recent introduction of EU traceability regulation it should be recognized that all efforts to design incentive compatible contracts are fruitless as long as traceability is not guaranteed. But even if traceability systems are in place, a probability $z < 100$ % may arise due to an insufficient performance of the documentation system. This could also simply be caused by the costs of tracing. Buyers may, e.g., be reluctant to *actually trace* less serious cases even if a complete *traceability* (understood as the ability to trace according to EC regulation 178/2002) is assured.

Besides considering these essential food risk features, a number of additional changes are made to the general discrete model (cf. e.g. Kreps, 1990, pp. 577) to account for the practical applicability and suitability of the model. For the sake of convenience, we provide a brief list of all the differences between our model and the standard PA-formulation:

1. The above-described binary perspective reduces the available set of actions to a_1 (non-compliance) and a_2 (compliance), and two corresponding effort levels ($k_1 < k_2$).

Likewise, only two quality outcomes ($y_1 < y_2$), and two remunerations ($w_1 < w_2$) are considered. This allows us to use simple binomial distributions (conditional on the two actions) for the stochastic variables outcome and remuneration.

2. Instead of assuming that the output can be verified without costs, we take the very characteristics of the food risk problem (credence qualities) into account and consider that observation is costly and that it can only take the form of sampling inspections carried out with an intensity $s \leq 100$ % (probability of random controls).
3. The standard PA-model does not account for multiple agent settings. Incentive problems resulting from incomplete output information are aggravated if identified properties are not retraced to a single supplier. We consider such situations which are frequently found in food chains by accounting for a tracing coefficient $z \leq 100$ %.
4. Instead of accounting for risk aversion endogenously, we assume risk neutral principals *and* agents in the model. Hence, optimal risk sharing will not be our concern. Due to costly and incomplete product inspection and tracing we nonetheless face the non-trivial problem of designing an optimal control and remuneration scheme.
5. Instead of accounting for a reservation utility μ, we normalize it to zero. This can also be seen as representing a situation with binding food processing regulations: if the agent does not participate (accept the contract), he does not have the choice to produce a low-price quality category, but has to refrain from production altogether.
6. Instead of accounting for a principal who maximizes his utility by selecting the agent's optimal action, we assume that he is a priori determined to induce compliance and only strives to do so at minimum costs. Hence, the second step of the optimization can be omitted and the problem is reduced to cost minimization for action a_2.

In the binary model (1) to (4), the conditional output probabilities ($\pi_{1,1}$ and $\pi_{1,2}$ for non-compliance, and $\pi_{2,1}$ and $\pi_{2,2}$ for compliance) coincide with the remuneration probabilities because the output can be directly observed and because it is unambiguously attached to the agent. In contrast to that, considering a control intensity $s < 100$ % as well as a tracing coefficient $z < 100$ % changes the expected remuneration for non-compliance $w(a_1)$ and for compliance $w(a_2)$. In other words, incomplete inspections in conjunction with traceability problems change the conditional payoff probabilities and increase the profitability of rule-breaking behavior. This reflects the fact that, independent of the (unknown) product quality, the principal has to pay the regular price whenever the quality is not explicitly ascertained through an inspection and whenever a detected irregularity is not traced back to its origin.

Instead of simply reformulating the model for the above-mentioned modifications, we now turn to table 1 which provides a handier notation for the binary food risk problem and which indicates the conditional payoff probabilities that result from the joint consideration of $s < 100$ % and $z < 100$ %.

Table 1: Notation for the binary food risk model

		s	control intensity = probability of random inspections ($0 < s \leq 100$ %)
		z	probability that responsible suppliers are traced ($0 < z \leq 100$ %)
w_1	=	$-S$	sanction (loss) inflicted on the agent if the undesired quality y_1 is detected
w_2	=	P	price paid for a product of the desired quality y_2
k_2-k_1=k_2	=	K	agent's cost of compliance with regulations [a]
π_{11}	=	r	probability of undesired quality y_1 conditional on action a_1 (i.e. non-compliance)
		szr	remuneration probability for $-S$ conditional on action a_1 (i.e. non-compliance)
π_{12}	=	$1-r$	probability of desired quality y_2 conditional on action a_1 (i.e. non-compliance)
		$1-szr$	remuneration probability for P conditional on action a_1 (i.e. non-compliance)
π_{22}	=	q	probability of desired quality y_2 conditional on action a_2 (i.e. compliance): $q > 1-r$
		$1-sz(1-q)$	remuneration probability for P conditional on action a_2 (i.e. compliance)
π_{21}	=	$1-q$	probability of undesired quality y_1 conditional on action a_2 (i.e. compliance)
		$sz(1-q)$	remuneration probability for S conditional on action a_2 (i.e. compliance)

[a] We replace k_2-k_1 by the costs of compliance K. It is unrealistic to assume that food business operators produce the unauthorized quality at cost $k_1 = 0$. For the sake of simplicity we normalize k_1 to zero and thereby avoid having to carry an extra variable through the analysis without impeding the general insights into the structure of the problem. A consideration of $k_1 \neq 0$ in applications will be easy. It is only necessary in normative analysis.

If we additionally consider the costs of control depending on the intensity $c(s)$ as well as costs for achieving different levels of traceability $c(z)$ and costs for imposing different sanctions $c(S)$, the principal's incentive problem needs to be restated as follows:

$$Min\big(w(a_2) + c(s) + c(z) + c(S)\big) = Min\big(P - sz \cdot (1-q) \cdot (P+S) + c(s) + c(z) + c(S)\big) \qquad (1')$$

$$s.t.\;\; w(a_2) - k_2 = P - sz \cdot (1-q) \cdot (P+S) - K \geq 0 \qquad (2')$$

$$w(a_2) - k_2 - w(a_1) = sz \cdot (q + r - 1) \cdot (P+S) - K \geq 0 \qquad (3')$$

$$0 < sz \leq 1$$

While there are only few parameters to be considered in the model, their empirical estimation still represents a formidable task in most practical circumstances.[2] It is not trivial, e.g., to define different control alternatives and to provide their cost estimates (let alone

[2] Monitoring the activities of suppliers instead of monitoring product properties can be seen as an attempt to get rid of foggy stochastic action-outcome linkages. Taking suppliers' action as the relevant outcome that is to be monitored directly makes the linkage deterministic. In this case, q and r can be equated to unity.

intensity-dependent control cost functions $c(s)$ for different control systems and technologies). In our subsequent case study, we therefore solely use (3') for the assessment of the current incentive situation and for a tentative investigation of incentive-compatible alternatives through variant calculations.

Perspectives of behavioral risk investigations

Investigations into behavioral risks can be related to the definition of the risk analysis process according to EU regulation EC 178/2002 which defines that "risk analysis means a process of three interconnected components: risk assessment, risk management and risk communication." While most food quality and safety analysts will associate the term "risk analysis process" only with technological hazards (i.e. unintentional technological and human failures), it needs to include moral hazards as well. Demanding integrated approaches which take account of all sources of risk is in line with Hennessy et al. (2003) who provide a typology of different sources for systemic failure in the provision of safe food and call for systems analysis approaches in the food safety context.

In behavioral risk analysis, risk assessment represents the positive part of the analysis which assesses the incentives that result, on the one hand, from the stochastic links between behavior and technological outcomes and, on the other hand, from the economic parameters. For behavioral risk communication, the PA-approach provides a clear conceptualization of the problem and a "language" for its perception and description, thus improving the interactive exchange of behavioral food risk findings among all stakeholders. Behavioral risk management finally represents the normative part of the analysis where the time horizon determines which parameters are "givens", and which are decision variables. In other words, it is the time perspective (cf. table 2) which decides whether variables are under the control of the designing principal and which determines whether a contract is considered to be optimal in the short, medium and long term. In table 2 as well as in the following section we assume that the production parameters, i.e. the costs of compliance K and the stochastic links between the agent's action and the outcome (represented by q and r) remain constant over all perspectives.

Table 2: Time horizon and decision variables in behavioral risk management

(i) Short-term perspective	(ii) Medium-term perspective	(iii) Long-term perspective
givens: $K, q, r, s, z, S_{up}, c(S)$ decision variables: P, [S]	givens: $K, q, r, c(s), z, S_{up}, c(S)$ decision variables: P, s, [S]	givens: $K, q, r, c(s), c(z), c(S)$ decision variables: P, s, z, S

(i) A short-term perspective can be seen as being equivalent to a given state of a control system (i.e. a given control intensity and traceability). (ii) In a medium-term perspective, it may be possible to change the control intensity by stocking up on control personnel and equipment. Solving the principal's constrained minimization problem consequently implies that control costs $c(s)$ are considered. (iii) In a long-term perspective, the traceability that results from the structure of transactions along the chain may e.g. be changed by restructuring efforts and by improvements to the documentation systems. This implies that traceability costs $c(z)$ for achieving different traceability levels are taken into account. In all three perspectives, it may be necessary to consider costs for imposing sanctions $c(S)$. Furthermore, it has to be considered that – at least in the short- to medium-term perspective – the sanction may be only partially under the control of the principal. This is indicated by the brackets in table 2.

Incentive-compatible remuneration and control schemes

We now carry through a model-based analysis and demonstrate how the binary moral hazard model (1') to (3') can be used for designing incentive compatible contracts in various situations. Considered situations differ with regard to their respective set of "givens" and "decision variables". Reducing the dimensionality of the problem, we only consider the remuneration costs $w(a_2)$ and the costs of control $c(s)$. For one thing, this is equivalent with a short- to medium-term perspective in which the traceability is a given parameter (see table 2). Furthermore, we treat the costs for imposing sanctions as being independent of the principal's incentive design, thus avoiding an extra variable in the analysis without impeding the insights into the structure of the problem.

Incentive-compatible schemes for a given control intensity and traceability

The first perspective is that there are given parameters K, q and r as well as s and z in the real world situation under examination. Aiming at specifying an optimal remuneration-formula, we only have to assume that both constraints of the minimization problem are binding. By treating (2') and (3') as equations and solving for P and S, we derive the following formula for P_{min} and S_{min}. They represent a solution to the incentive problem which induces compliance at minimum remuneration costs $w(a_2) = K$:

$$P_{min} = K \frac{r}{q + r - 1} \tag{5}$$

$$S_{min} = K \frac{1 - szr}{sz(q + r - 1)} \tag{6}$$

Binding constraints imply agents who are indifferent between participating and not participating as well as between high and low effort levels. With risk-averse agents both constraints are binding in the optimal solution (Kreps, 1990, p. 588). If principal and agent are risk-neutral, we do not need to consider optimal risk sharing. In other words, the incentive compatibility constraint (3') is not binding any more and alternative optimal solutions (with increased incentives to put in high effort) can be found. At the same time we can assure that the expected remuneration does not increase by continuing to use an equation instead of inequality (2'). That is, the levels of S and P may be increased simultaneously according to the following function which we derive by simply converting (2'):

$$S(P) = \frac{K-P}{sz(q-1)} - P, \text{ with } P \geq P_{min} \tag{7}$$

Higher values than P_{min} and S_{min} according to (7) represent minimum remuneration cost solutions whenever $q < 1$ because the effect of a price increase is counter-balanced by an increase of the sanction. In the case of deterministic outcomes of compliance ($q = 1$), however, all prices exceeding $P_{min} = K$ will necessarily increase remuneration costs. At the same time the sanction S may reach infinity. The latter effect can be used to design "boiling-in-oil-contracts" (cf. Rasmusen, 1994, p. 180): very high sanctions inflicted for outputs which show without doubt that the agent is not complying achieve a first-best solution even for risk-averse agents because complying agents have nothing to fear.

Incentive-compatible schemes for a given traceability and sanction limit

As a rule, sanctions cannot be chosen freely by the principal, e.g. due to legal restrictions concerning the admissible sanction level, especially in cases where no clear-cut proof can be found for deviant behavior. That is the reason why we adopt an alternative perspective now: we take account of an upper sanction limit S_{up} and consider the control intensity s as a decision variable. After empirically estimating the relevant parameters K, q, r, z, and the sanction limit S_{up}, the minimum control intensity is derived by converting (6) and accounting for the fact that the range of values for the control intensity is limited to $0 < s \leq 1$:

$$s_{min} = \min\left(\frac{K}{z(S_{up}(q+r-1)+Kr)}; \quad 1 \right) \tag{8}$$

All parameter constellations leading to computed values $s_{min} \leq 1$ according to the first argument of the min function given in (8) allow for a minimum remuneration cost solution in terms of a combination of P_{min} and s_{min} which induces compliance exactly at costs K. However, all constellations where the first argument in (8) yields values greater than unity prevent the minimum remuneration cost solution. More generally put: any limit S_{up} which forces the first argument to be greater than a given control intensity requires the principal, who wants to induce compliance, to increase the price. After equating (3') with zero and after a simple conversion of the equation, we are able to determine the necessary price P which induces the agent to comply in both situations:

$$P = \begin{cases} \dfrac{K}{sz(q+r-1)} - S_{up}, \quad if\ s < \dfrac{K}{z(S_{up}(q+r-1)+Kr)} & \text{(9a)} \\ \dfrac{K}{sz(q+r-1)} - S_{up} = P_{min}, \quad if\ s \geq \dfrac{K}{z(S_{up}(q+r-1)+Kr)} & \text{(9b)} \end{cases}$$

Equation (9) reflects the connectivity of sanction, control intensity, and price: being faced with an upper sanction limit and wanting to meet the incentive compatibility, there is a critical control intensity which needs to be met or exceeded if the principal does not want to increase the price above its minimum level (see situation b). If the critical control intensity is met, the upper sanction limit coincides with the minimum sanction required according to (6). Falling below that critical control intensity without being able to increase the sanction above the level of S_{up} (see situation a), however, requires the principal to increase the price in order to ensure the incentive compatibility. If the principal pays less than P according to (9a), profit maximizing agents will not comply because the incentive compatibility constraint is not met.

Following (1'), remuneration costs inducing compliance are known to be computed as:

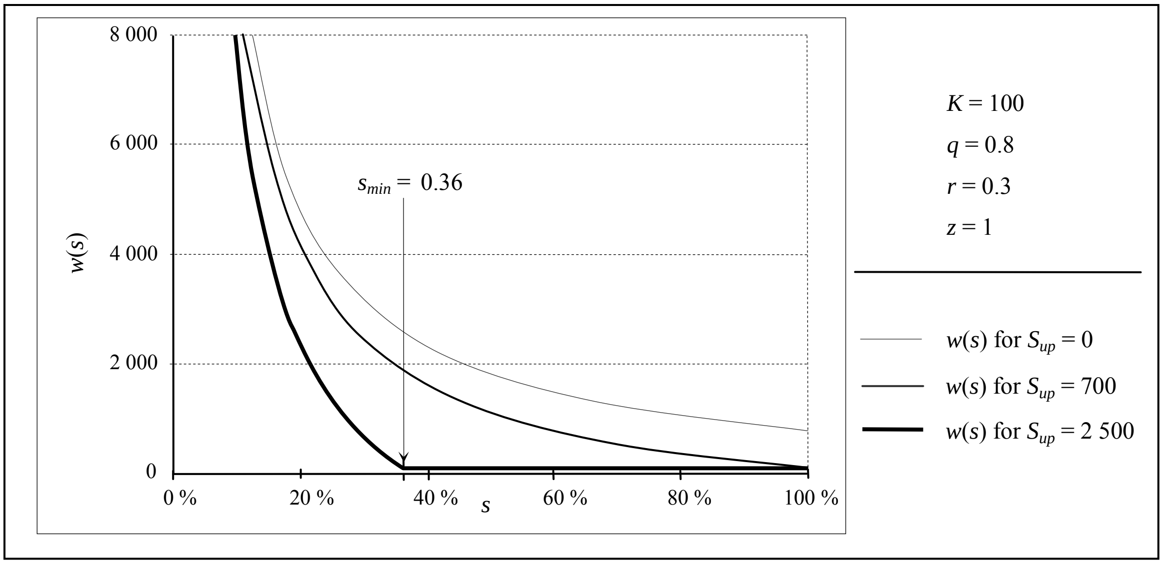
$$w(a_2) = P - sz(1-q)(P+S) \tag{10}$$

According to (9a) and (9b), for a given sanction limit, the price which meets the incentive compatibility constraint depends on the control intensity. Consequently substituting (9a) and (9b) into (10) and using $w(s)$ instead of $w(a_2)$, we derive the following remuneration cost function depending on the control intensity s:

$$w(s) = \begin{cases} \dfrac{K}{sz(q+r-1)} - S_{up} - \dfrac{(1-q)K}{q+r-1}, \quad if\ s < \dfrac{K}{z(S_{up}(q+r-1)+Kr)} & \text{(10'a)} \\ K, \quad if\ s \geq \dfrac{K}{z(S_{up}(q+r-1)+Kr} & \text{(10'b)} \end{cases}$$

(10'a) and (10'b) demonstrate that, with a given sanction limit, remuneration costs of the cheapest system which induces compliance become a function $w(s)$ of the control intensity. Figure 1 illustrates the nature of the remuneration function by referring to a demonstration setting: with the severe limit $S_{up} = 0$, there is no intensity s which allows for the minimum remuneration cost solution $w(s) = K = 100$. Instead, the remuneration has to be computed according to (10'a) on the full range of $0 < s \leq 1$. With less severe limits than $S_{up} = 700$, there are minimum control intensities s_{min} according to the first argument in (8) above which we can find optimal combinations of sanction and control which do not exceed minimum remuneration costs $w(s) = K = 100$ (e.g. $s_{min} = 0.36$ for $S_{up} = 2\,500$).

Figure 1: Remuneration cost functions $w(s)$ depending on the control intensity s.



Optimal schemes for a given traceability, sanction limit, and control cost function

We now explicitly account for control costs. Our perspective is that we have given parameters K, q, r, z, S_{up}, and a control cost function $c(s)$. Costs of imposing sanctions below the upper sanction limit S_{up} are still considered constant. Again, the optimal control intensity and price need to be determined. Following (10'a) and (10'b), remuneration costs - in the case of a given sanction limit S_{up} - are a function of the control intensity. Hence, the total costs of the incentive and control system depending on the control intensity are:

$$TC(s) = w(s) + c(s) \tag{11}$$

Consequently, the principal's optimization problem can be solved by minimizing the function $TC(s)$. However, we must account for the fact that the remuneration function has a decreasing part (10'a), and a constant part (10'b). In contrast to that, we assume a strictly increasing (linear) control cost function $c(s) = Cs$, where $C = dc/ds$ are the costs of complete inspection. After differentiating (10'a), we know that an intensity $\hat{s}$ which meets the following equation on the decreasing part of the remuneration function represents a solution to the cost minimization problem:

$$-\frac{dw}{ds} = \frac{K}{\hat{s}^2 z(q+r-1)} = \frac{dc}{ds} = C \quad \Rightarrow \quad \hat{s} = \sqrt{\frac{K}{z(q+r-1)C}} \tag{12}$$

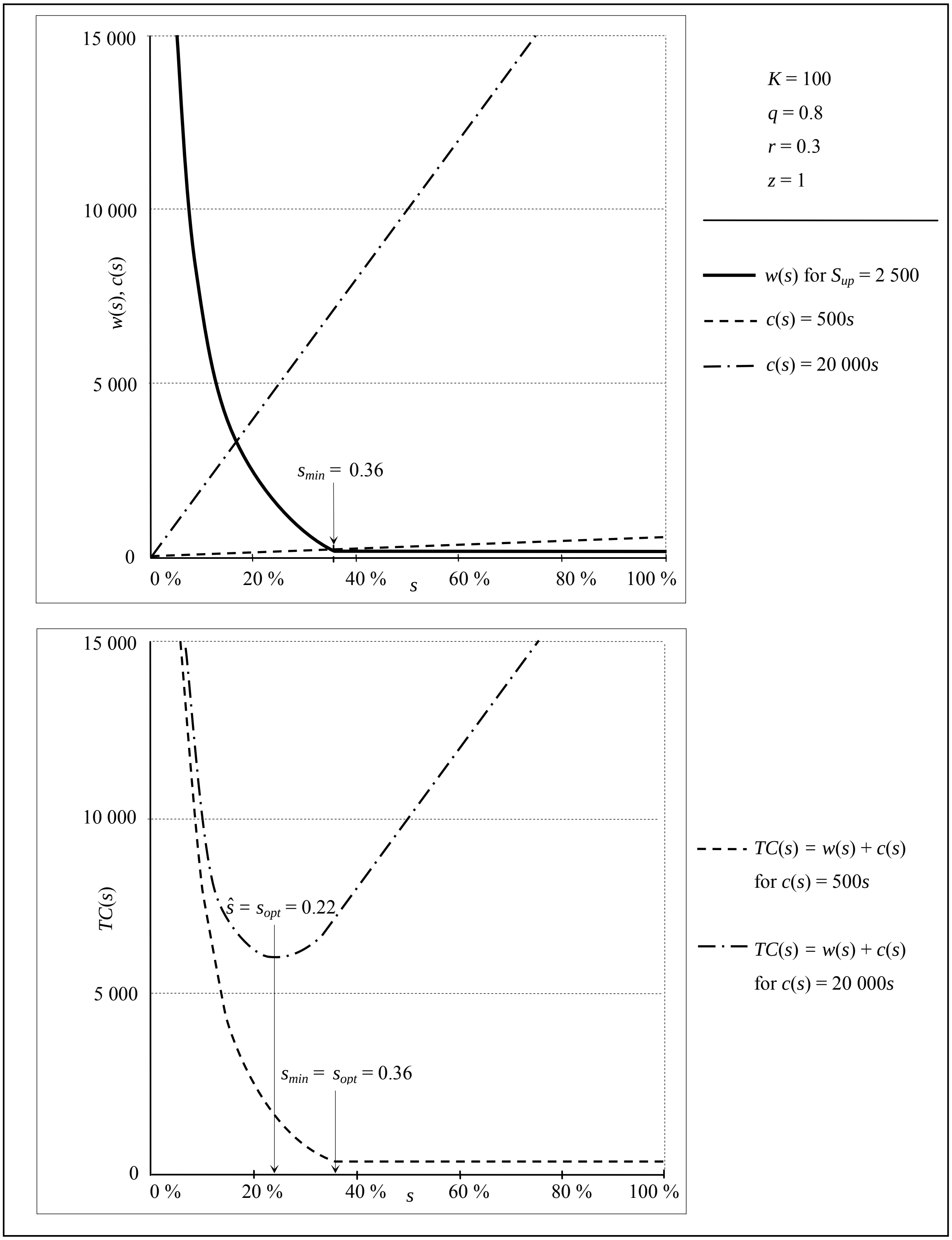
If the positive slope of a strictly increasing control cost function does not equal the negative slope of the remuneration function on its decreasing part (this may e.g. be the case for low costs of control), there is no solution $\hat{s}$ on the decreasing part. Consequently, the optimal solution is simply given by s_{min} according to (8). Thus, in the case of a strictly increasing control cost function the optimal control intensity s_{opt} is given by:[3]

$$s_{opt} = \min(\hat{s};\ s_{min}) \tag{13}$$

Referring again to our familiar demonstration setting, figure 2 visualizes that the optimal control intensity ($\hat{s}$ or s_{min}), which leads to a minimum of the total costs of the incentive and control system $TC(s)$ according to (11), depends on the slope of the control cost function relative to the slope of the remuneration function. We consider the remuneration function resulting from a given sanction limit $S_{up} = 2\,500$. In combination with a high gradient of the control cost function ($Cs = 20\,000s$), the control intensity $\hat{s} = 0.22$ represents the optimal solution. In combination with a low gradient ($Cs = 500s$), however, the control intensity $s_{min} = 0.36$ is optimal. After determining s_{opt}, the price P is to be determined according to (9) in order to ensure incentive compatibility.

[3] If the control cost function is not strictly increasing in s we need to determine explicitly the minimum of the total cost function $TC(s)$, instead of resorting to (13). This may be relevant if we consider "reduced damages" which increase (in a linear fashion) in s because the more harmful products are sorted out the more the control intensity is increased. Considering "reduced damages" in combination with an "isolated control cost function" with a decreasing positive slope (e.g. due to economies of scale), the resulting (effective) control cost function may have a maximum on $0 < s \leq 1$.

Figure 2: Remuneration function ($w(s)$, control cost function $c(s)$ and resulting total cost function $TC(s)$.



Long-term effects of system innovation and structural change

So far, the question of long-term system changes has not been considered. Taking the long-term perspective means thinking about the comparative costs of different institutional environments and about systems innovations in terms of collective choice or investments into new structures (cf. Ostrom, 2005). This could, e.g., involve the following changes: (i) introducing new production technologies that alter both the compliance costs K and the probabilities q and r which link action to outcome, (ii) altering the upper sanction limit S_{up} by lobbying for an increase of legal sanctions, (iii) adapting the degree of vertical integration as well as improving documentation and therefore changing the traceability z, (iv) changing the modes of control (control technologies, control points etc.) and therefore the control cost function $c(s)$, (v) moving away from spot markets altogether and introducing, e.g., contracts with tournaments, etc.

In other words: in the long run structural parameters may become decision variables. This gives rise to the question which type of innovation might represent a good investment. Before making decisions, different alternatives of action need to be defined in a decision-oriented planning approach. That is, searching for the long-term optimal incentive and control system, one needs to conceive and model a limited number of discrete organizational alternatives which are viable and "make sense". Then, within each alternative the optimal contract needs to be determined. Afterwards, the alternative can be identified which presumably induces compliance at lowest costs. Of course, in such a comparison annualized investment costs for changing system structures etc. need to be considered.

Case study: situational incentives of grain farmers after fungicide use

Aiming chiefly to demonstrate the functionality of the developed binary model, we resort to a small case study instead of collecting data in an extensive survey. The case study considers the incentives of grain farmers regarding the minimum waiting period after fungicide use. While applying critical value analyses to identify contracts that get incentives "right", we do not optimize the system as a whole. That is, we do not consider control cost functions, traceability cost functions etc. We only estimate (and vary) the parameters K, q, r, s, z, P, and S and use equation (3') to quantify resulting incentives.

The situational background

Grain farmers regularly spray fungicides five to six weeks before harvesting. Applied products are labeled for control of fungal infections that could reduce the grain quality and quantity. Profit maximizing farmers might be tempted to breach the waiting period of 35 days if, a few days before its expiration, the weather is ideal for harvesting.

The farmers considered in the case study sell their wheat to a grain dealer who takes and stores samples from all individual trailer loads, tests them for technological qualities (humidity, protein content etc.) and differentiates prices for different quality categories. Before testing for pesticide residues, the grain dealer blends the "loads" from different farmers into "batches". Residues are thus only monitored at downstream control points and infringements are only detected if blended batches exceed the tolerance standards. This happens only if a critical number of farmers simultaneously break the rule. Otherwise, pesticide loads are "sufficiently" diluted and free-riders stay undetected. Regarding the resulting increase of the residue level, one might say that free riders "move the distribution of this undesirable outcome to the right". The free-riding opportunity arises precisely because the confided group appears trustworthy on the whole, but is in fact (morally) heterogeneous.

In the considered case we are not facing a collective reputation problem in the sense of a dynamic common property resource problem. This would imply that reputation is "extracted" from the collective reputation stock through malpractice (cf. Tirole, 1996; Winfree and McCluskey, 2005). In contrast to such an erosion of collective reputation, we may reasonably assume a constant level of group reputation when looking at the farmers' incentives: if few farmers cheat, no irregularities at all are found in blended batches due to dilution; if many farmers cheat, tolerance levels are exceeded, but the individual behavior will then be perfectly observed because the stored individual samples are tested. The fear of exclusion from the group, however, is a relevant incentive to comply with rules and sustain individual reputation (cf. Tirole, 1996) because farmers anticipate that they face less favorable trading conditions (i.e. long-term market losses) than rule-abiding group members once individual rule-breaking has been found out.

Assessing farmers' situational decision parameters

The parameters determining the farmers' incentives were assessed in interviews with three farmers from Brandenburg, Germany (see table 3). Additionally, the grain dealer was interviewed. The interviewees assessed the parameters for four discrete types of weather, implying, in turn, four different technologically optimal harvest dates: 10 days, 6 days and 2 days prematurely as well as an optimal harvest date after the expiration of the waiting period. The term "technologically optimal" implies that, without a prescribed waiting period, a farmer would harvest because he expects economic losses due to a reduced quality, quantity, and/or increased costs for any posterior date.

Table 3: Parameters determining the incentive situation perceived by interviewed farmers

	x-days	Farmer A	Farmer B	Farmer C
Action-outcome linkages (*r* and *q*)	10	r = 15 %	r = 95 %	r = 33 %
probability that the farmer exceeds the residue	6	r = 5 %	r = 50 %	r = 20 %
limit in his individual load if he harvests x-days	2	r = 0 %	r = 0 %	r = 0 %
prematurely	0	1-q = 0 %	1-q= 0 %	1-q = 0 %
Detection probability (*s*) probability that an irregularity is detected if the farmer's individual load exceeds the residue limit		5 %	50 %	5 %
Compliance costs (*K*) losses in sales and additional costs (€/ha) if the	10	200	260	200
waiting period is met in spite of weather conditions making it optimal to harvest x-days prematurely	6	100	130	100
Immediate market losses (*P*) losses in sales and subsidies (€/ha) if non-compliance is proven		984	984	984
Sanction (*S*) monetary losses (€/ha) if non-compliance is proven		1 100	20 750	13 375
thereof: - short-term sanctions (fines, damages, …)		350	20 000	13 000
- capitalized long-term market losses		750	750	375
Tracing probability (*z*) a farmer's probability to be traced if an irregularity of the product has been detected		100 %	100 %	100 %

Table 3 summarizes the parameter values that are attached to the offence-prone regulation "waiting period" according to the perception of the interviewed farmers. We hereafter comment shortly on these parameters. If appropriate, we focus on farmer A.

Action-outcome linkages (*r* and *q*): all farmers think that, in case of compliance, they run no risk at all to exceed the residue limit in their grain (1-q = 0 %). They all trust that a safety margin is built into the prescribed waiting period and agreed that harvesting two days early would still involve a zero probability of exceeding the limit. According to this perception, a 2days-infringement of the waiting period has the same results as compliance (r = 1-q = 0 %). The farmers' assessments of the decomposition process before that date differed widely. Farmer A thinks that a 6days- (10days-) infringement increases the probability of exceeding the limit to 5 % (15 %). In wide contrast to that, farmer B, e.g., believes this probability to rise to 50 % (95 %).

Detection probability (*s*): avoiding the introduction of an additional symbol, s is to be interpreted as the probability that a product irregularity is detected at the control point "blended batch" conditional on having exceeded the residue limit in the individual load. This probability results from (i) the control intensity (i.e. percentage of blended batches that are controlled), and (ii) the dilution effect (i.e. the fact that excessive individual pesticide loads may be "sufficiently" thinned down). All farmers ignored the actual control intensity as well as the details responsible for the dilution effect such as their share in a blended batch and the behavior of other farmers who contribute to a batch. However, they provided (widely differing) ad hoc estimates regarding the joint effect of both factors.

Compliance costs (*K*): reduced sales resulting from suboptimal harvest dates are treated as opportunity costs: expected losses are mainly due to a threatening decline of quality. If it is technologically optimal to harvest 10 days (6 days) early, farmer A expected a loss of sales of 175 €/ha (87.5 €/ha) due to a degradation from food to feed grain quality. Furthermore, he expects machinery costs to increase by 25 €/ha (12.5 €/ha) if he were to harvest 10 days (6 days) later than optimal.

Immediate market losses (*P*): all farmers are convinced that they would completely lose their income from the wheat sales (including EU-subsidies) of $P = 984$ €/ha if non-compliance was detected.

Sanction (*S*): farmer A estimated that he would have to pay an equivalent of 350 €/ha in short-term sanctions in case of detection. In addition, he expects that his capitalized future disadvantage on the market (loss of negotiating power) would amount to 750 €/ha of wheat. Farmer B's and farmer C's perception of comparably very high sanctions is due to their understanding that they would be forced to pay damage compensations for large amounts of grain if these were contaminated by their individual load.

Tracing probability (*z*): all farmers believe that the stored individual samples are tested and that individual loads are unambiguously traced if irregularities are found in the blended batch ($z = 100\%$).

Investigating farmers' incentive situations

Table 4 shows the incentive situation which - according to (3') - results from the farmers' perception of parameters. Results are indicated for the two weather types that favor most premature harvest. Risk aversion is not endogenously accounted for. This does not represent an abstraction from farmers' risk attitudes. Risk attitudes are considered exogenously by the way data were obtained: risk-averse farmers implicitly increased cost-benefit ratios when answering questions with regard to decision parameters (i.e. risk premiums are deducted already). Thus, the problem of estimating risk utility functions does not arise.

Table 4: Economic inferiority (–) / superiority (+) of complying with the waiting period according to the perception of parameters by interviewed farmers (€/ha)

Weather type	Technological optimal harvest date	Farmer A	Farmer B	Farmer C
I	10 days premature	– 184	+ 10 064	+ 39
II	6 days premature	– 95	+ 5 304	+ 44

Only farmer A perceives an economic reason to breach the waiting period. Using the parameters for weather type I as assessed by the farmers, we identify - by means of critical value analyses - which change of contract conditions (sanctioning, controls) would ceteris paribus ensure/maintain incentive-compatible contracts. In the example under consideration, the participation constraint (2') does not need to be considered in the critical value analysis. In contrast, it is possible to design "boiling-in-oil-contracts" (cf. Rasmusen, 1994, p. 180). Since the probability of the desired product quality for complying farmers is $q = 1$, they are neither affected by increased sanctions nor by intensified controls. Examples of contracts which get the incentives "right" are given in table 5.

Table 5: Incentive-compatible contracts for weather type I

	Farmer A	Farmer B	Farmer C
Critical sanction with retention of the present system of downstream controls (blended batches)	25683 €/ha	no sanction needed	11016 €/ha
Critical sanction after introduction of complete upstream controls (individual loads)	349 €/ha	no sanction needed	no sanction needed
Critical control intensity of individual loads with present sanctions: A: 1100 €/ha, B: 20750 €/ha, C: 13375 €/ha	64 %	1.3 %	4.2 %
Critical control intensity of individual loads with assumed sanctions: A: 2200 €/ha, B: 41500 €/ha, C: 26750 €/ha	42 %	0.6 %	2.2 %

In the present control regime and with weather type I, the sanction as perceived by farmer A would need to be increased from its present level of 1 100 € to over 25 000 € per hectare in order to eliminate his 184 €-per-hectare temptation to break the rule. Since it is not realistic to assume that the principal succeeds in increasing the sanction to this level, we consider the impact of applying complete residue controls to individual loads. This is equivalent to replacing downstream control points (blended batches) by upstream control points (individual loads), thus eliminating the dilution effect, and raising the probability that an objectionable load is detected from the perceived level of $s = 5$ % to 100 %. Now, a sanction of approximately 350 € per hectare would suffice to eliminate misdirected economic incentives. Alternatively, with the presently perceived sanction level of 1 100 € per hectare, it would be sufficient to analyze 64 % of individual loads. Considering farmers B and C reveals that the incentives "in force" are in the eyes of the beholder. Farmer B, e.g., perceives no economic temptation whatsoever to break the rule, mainly because he believes economic losses resulting from detection to be very high.

The grain dealer's view is summarized briefly: he believes that, in the present system of downstream controls, a rule-breaking farmer's risk of being detected is almost zero due to the dilution effect. The grain dealer is convinced that situational incentives are indeed not "right". According to his interview statement, he relies on character trust.

Abstracting from individual settings, we can generalize from the last row of table 5 that increasing the sanction level allows for a decrease of the control intensity without compromising the incentive compatibility. There is an optimal combination to be found which depends on the costs of analytical controls on the one hand, and the costs of increasing effective sanctions (lawyers, lobbying for sanctions etc.) on the other hand.

The essence of this case study can be pictured through the following typology: (1) the one extreme is a farmer who is utterly trustworthy. Because of his personal set of preferences he resists every economic temptation to break the rules. (2) The other extreme is a farmer who is only trustworthy if, given his exclusive objective of profit-maximizing, the situational incentives are "right". (3) Between these two extremes is the mixed-type farmer who accepts a profit trade-off in exchange for a feeling of moral integrity, but yields to rule-breaking if the additional profits exceed his personal resistance.

It is common sense to assume that real decision-makers are of mixed-type. They will differ, however, with regard to their personal resistance to economic temptations. Taking into consideration that economic parameters may also differ from one agent to the other and that they are seen through the eyes of the beholder, some farmers may perceive economic temptations to break the rules; others may not. Amongst the former some may break the rules; others may not. Thus, finding the optimal contract design is not easy: every buyer (principal) will have difficulties in gaining information about how heterogeneous suppliers (agents) assess the relevant parameters. An even greater obstacle will be to gain knowledge about their individual characters. Hence, the only practical way to decrease the probability of rule-breaking is to increase situational trust by "moving into the right direction" and increasing the levels of those parameters that promote compliance.

Concluding comments

In this article a principal agent model has been adjusted to the characteristics of behavioral food risks. This model has the capacity to account for incomplete inspection of the product quality as well as for limited possibilities to trace a product to its origins. Its manageable data requirements qualify it as a starting point for the specification of models tailored to the empirical analysis of particular activities in food chains. Its practical approach has been demonstrated through a case study from primary grain production.

Future lessons with regard to the integration of behavioral food risk analyses into comprehensive risk approaches may be learned from the widely established HACCP-system. According to its seven principles, its users are (1) to analyze their operations and to prepare a list of potential hazards, (2) to determine "critical control points" where these hazards can be controlled, (3) to define adequate tolerance limits, (4) to establish adequate monitoring procedures, (5) to define corrective measures in case deviations are identified, (6) to document all HACCP steps, and (7) to verify that the system is working correctly.

So far, HACCP is limited to the prevention of unintentional technological and human failures. In the framework of a comprehensive risk analysis system, behavioral risks could be managed by using similar principles. That is, in addition to managing the risk of unintentional failures within one's own operation, one could systematically aim to reduce behavioral risks that result from information asymmetries in transactions with suppliers. This requires the definition of critical control points and adequate monitoring procedures with regard to risks arising from malpractice of opportunistic suppliers. Our case of grain producers has shown, e.g., that some control points (i.e. monitoring residues in blended batches of grain) are less suited to manage behavioral risks than others (i.e. monitoring residues in individual loads of grain).

A behavioral risk management system could be termed "moral hazard analysis and critical control points system" (M-HACCP). On the one hand, a mandatory introduction could be seen as an attempt to mitigate the externality problem which arises if buyers are not motivated to reduce downstream diseconomies and to manage moral hazard when purchasing inputs. On the other hand, legal liabilities and reliable traceability systems will add to buyers' own motivation to search for incentive-compatible contracts. The case study demonstrates, however, that this may not suffice if residue levels, while being increased due to malpractice, are thinned down due to commingling of products from different origins. The introduction of M-HACCP could also be achieved through private contracts if this is considered useful by food chain actors for competitive reasons. Highly integrated food chains such as the Danish pork industries could be seen as an example.

If buyers are motivated to manage behavioral risks on the part of their suppliers, they will try to reduce downstream diseconomies (and finally consumers' exposure to increased residue levels) by trying to reduce the incidence of undesired qualities which result from opportunistic behavior of suppliers. Obtaining direct access to their suppliers' HACCP and using existing documentation and paper trails from suppliers' HACCP systems will lower the costs of behavioral risk management and provide additional non-product control points and insights in behavior.

Several questions arise in connection with an envisaged introduction of an M-HACCP system: would its adoption as a regulatory standard be a cost-effective measure to eliminate behavioral risks? Should its design be left entirely to food business operators or should its introduction be combined with an external specification of standards that are justified by a publicly desirable level of risk reduction (see e.g. Unnevehr and Jensen, 1999, for a discussion of analogous issues in connection with HACCP)? Knowing that neither HACCP nor M-HAACP systems as such replace the need to weigh the potential benefits from increased quality against its costs, what are the costs and benefits of various system specifications (nature and number of control points, type of controls including direct monitoring of suppliers' activities etc.)?

Especially the evaluation of the benefits of behavioral risk management will be difficult in practice due to the lack of reliable evidence and data. Furthermore, the extension of behavioral food risk analysis to other food chain activities may require that the structure of the behavioral risk model is developed further and extended with regard to its restrictive assumptions. Depending on the situation, the following extensions might be promising: (i) instead of a binary perspective according to (1) to (4), finer partitions of the agent's scope of action such as different degrees of compliance could be accounted for; (ii) instead of considering one common set of outputs both for compliance and for non-compliance, different sets or probability distributions for continuous output values could be considered; (iii) instead of assuming a non-ambiguous observation of the output, a statistical measurement error rate could be estimated which would allow for an appraisal of first and second degree errors. However, before increasing the complexity of applied models, one should always check whether informational gains justify additional costs.

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