MODELLING THE EFFECTIVENESS OF CROSS-COMPLIANCE UNDER ASYMMETRIC INFORMATION

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Abstract

The effects of cross-compliance depend on the strategies of participation/compliance of farmers, as well as on the ability of public administration to design appropriate mechanisms of control and sanctions. The objective of this paper is to present a reference framework for the analysis of cross-compliance under asymmetric information and to test the empirical relevance of the problem. The methodology is applied to a case study represented by the province of Bologna (Italy).
The results show that, in the present conditions of control and sanctions, only a small share of farms is interested in complying with cross-compliance. The profitability of the choice of compliance/non-compliance depends mainly on the amount of single farm payment entitlements compared with the total land.. The main message, however, is that, in order to increase effectiveness, environmental prescriptions as well as control effort should be considered as a variable to be adapted to incentive compatibility criteria.

Key words: Cross-compliance, asymmetric information, Single farm payment

1. Objectives

The effects of cross-compliance, introduced with the reform 2003 of the CAP, depends on the strategies of participation/compliance of farmers, as well as on the ability of public administration to govern such phenomena through appropriate mechanisms of control and sanctions. Cross-compliance is a structural part of the present EU policy and is likely to maintain a major importance in the future EU policy strategy (European Commission, 2007b). However, the ability of cross-compliance to achieve environmental objectives and the costs of such achievements are still largely unexplored. The expectations and assumptions about the ability to control compliance affects both the evaluation of its outcomes and the consideration of future design options. In this paper we address the issue of optimal cross compliance design when diverse agents can cheat and control is costly.
The objective of this paper is to present a reference framework for the modelling of cross-compliance and for the design of cross-compliance under asymmetric information, and to test it empirically. The empirical application is also used in order to test the relevance of the problem.
This paper first develops a model of optimal control effort, based on the logic of the principal-agent approach under moral hazard. Then the model is tested using empirical information from an area of Emilia-Romagna (Italy).
The remainder of the paper is broadly divided into four parts. Section 2 gives account of the literature related to the issue of cross compliance under asymmetric information. A model of cross compliance is presented in section 3, followed by the results in section 4. The paper ends with some discussion in section 5.

2. Moral hazard issues in cross-compliance

The incentive mechanism adopted in cross-compliance relies on the threat of a sanction (reduction of payment) in case non-compliance is detected.

It is a widespread expectation that in many cases this mechanism will not work, either because of the insufficient controls or of the difficulties in detecting non-compliance. However, if the control/sanction mechanism works, the environmental effects are still conditioned to the ability of the payment to cover the costs of compliance. Farmers could prefer to give up the payment rather than have to comply with cross-compliance prescriptions. This consideration may be of major importance where payments are distributed in very small amounts by farm, as in Italy (European Commission, 2007a)

The information situation of the decision maker can be examined, in economic terms, under the heading of asymmetric information, with both moral hazard (possibility of cheating) and averse selection (unknownly differentiated agents).

This problem is to a large extent not addressed in the literature on cross compliance, in spite of its practical importance. Previous works on cross-compliance and the administrative costs of the CAP have already highlighted the role of controls and their costs (Bennet et al., 2006; European Commission, 2007c). The understanding of these issues may be relevant either in the ex-ante stage, in order to design appropriate incentive mechanisms, and in the evaluation stage, in order to take properly account of the most likely additional environmental effects of cross-compliance.

As incentive mechanisms are concerned, the issue of appropriate level and targeting of monitoring/control activities is a crucial one. Targeting of control activities may be based on past performance or on an ex ante announced concentration of monitoring effort on some sub-groups of agents (Fraser and Fraser, 2005). According to Fraser and Fraser (2005) a robust theoretical background to a higher targeting of resource for controls do exist and this have can potentially contribute to alleviate the moral hazard problem (Fraser, 2004).

However, also tailoring of prescriptions in relation to payments and to environmental priorities have a clear role in policy design (Claassen, 2005).

Related literature in the field of agriculture has mostly concerned voluntary agri-environmental schemes and related policy parameters, including mechanism design or compliance monitoring design Latacz-Lohmann (2004).

Based on a wide stream of general economic literature (Laffont and Martimort, 2002), the problem of moral hazard in agricultural policy has been developed in recent years by a few papers (e.g., Choe and Fraser, 1998; 1999), assuming the possibility of sanctions connected to the detection of non-compliance through monitoring, which effect is to increase the probability that the fraud is detected. Less frequently moral hazard is considered together with adverse selection (e.g., White, 2002). Fraser (2004) develops a model when the design of targeting and compliance controls are considered together and in an intertemporal framework.

These papers emphasise the importance of adequate systems of monitoring and sanctions. However, the mechanisms for non compliance are much more complex than these. For example there may be lack of information among farmers. Also, farmers may be different in terms of attitude to cheating or being honest, with implication for the optimal policy design and for the probability of non-compliance (Hart and Latacz-Lohmann, 2005). Risk aversion may also have a role here (Fraser, 2004).

Building on this bundle of literature, this paper adopts a principal agent structure, with possibility of non-compliance and differentiated agents. However, contrary to most asymmetric information literature, we assume that non-compliance can be perfectly detected with a sufficient level of control/sanctions and that the differences between farmers only concern the amount of payments and farm size, known to the public administration.

3. The model

We model compliance to a generic set of prescriptions through a continuous variable $e_i = [0-1]$, where *e* represent the degree of compliance and *i* represent the farm type. The cost of compliance is represented by a function $\Psi_i(e_i)$, with $\Psi_i'(e_i) \geq 0$, $\Psi_i''(e_i) \geq 0$, and $\Psi_i(0) = 0$, $\Psi_i'(0) = 0$, $\Psi_i''(0) = 0$. Hence both the level of compliance and its cost may be different in different farm types and the cost increases more than proportionally with the increase of the level of compliance.
The farmer receives a payment P_i determined by his historical payment entitlements. In case he is not compliant, a sanction is raised. The sanction is calculated as a function of the payment, ρP, where ρ represent the share of payment subtracted as a sanction. This parameter may be treated as a policy design variable, as the regulator may have the option of changing/adapting its value to encourage compliance, also by differentiating it across farms. However, as this may create political/equity difficulties we assume it cannot be differentiated among farms. Also, as punishments for non-compliance relate to the right to receive the payments, in the model we always assume that $\rho \leq 1$.
The probability of non-compliance being detected depends on a number of parameters, including some random effects (e.g. mistakes or weather conditions). We simplify the problem by calculating the probability of the non-compliance being detected based on two parameters: non-compliance (directly correlated) and monitoring (inversely correlated). We assume that the probability that non compliance is detected, if some non compliance exists, is equal to the degree of non-compliance ($1-e_i$).
Monitoring intensity (m_i) is the expectation that a farm is monitored and may derive by the announced percent of farms monitored each year. It can take a value between 0 and 1 and can be differentiated by farm. We use it as a direct representation of the probability that a non-compliance is detected. In other words, in any farm monitored, if it is non-compliant, non compliance is detected with probability $1-e_i$ and the total probability that non compliance is detected is equal to $m_i(1-e_i)$.
Under this assumption, the problem of the private optimal level of cross-compliance may be written as:

$$\text{Max } \pi_i = ((1-m_i)+m_i e_i)(P_i - \psi_i(e_i)) + (m_i(1-e_i))(P_i - \rho P_i - \psi_i(e_i)) \quad (1)$$

The profit of the farm *i* (π_i) is determined by two components: the profit in case the non-compliance is not detected and the profit in case the non-compliance is detected, each one multiplied by the respective probability. Note again that the probability of each event is determined by the monitoring level and the degree of compliance and there is no a further stocasticity due to errors in detection or other factors.
The possibility that the farms considers the costs of compliance too high and decides to give up the payment is not considered here. This is motivated by the fact that considering $\rho \leq 1$ and likely $m_i \leq 1$, such option will always yield a lower result compared with staying in the payment scheme and give up (part of) the payment only if the non-compliance is detected. Note that this does not apply

anymore in case $\rho > 1$, as the sanction could produce a cost beyond the payment and would be potentially profitable to stay out of the scheme in order to avoid such cost.

We first note that $\left((1-m_i)+m_i e_i\right)$ and $\left(m_i(1-e_i)\right)$ are complements to one, which simplifies the profit function to:

$$\pi_i = P_i - \psi_i(e_i) + \left(m_i(1-e_i)\right)\left(-\rho P_i\right) \tag{2}$$

Taking derivatives for e and first order conditions, this yields:

$$\frac{\partial \pi_i}{\partial e_i} = -\psi_i'(e_i) + m_i \rho P_i = 0$$

Which yields:

$$\psi_i'(e_i) = m_i \rho P_i \tag{3}$$

The optimal level of compliance depends on monitoring, degree of sanction and payments. When any of the three is zero, the cost of compliance (hence compliance) will be zero.

Let us now define a function *f*, such that $f_i\left(\psi_i'(e_i)\right) = e_i$. This is the inverse function of the cost function. It may also be written as:

$$f_i\left(\psi_i'(e_i)\right) = f_i\left(m_i \rho P_i\right) = e_i \tag{4}$$

Taking now the point of view of a public administration, we consider the problem of maximising the welfare produced by the policy, by identifying optimal policy parameters. In principle the environmental value of cross-compliance, farmers' cost of compliance and shadow cost of public funds should be considered here. However, assuming a local administrative body in charge of cross compliance implementation, the problem could be largely simplified. In particular, as payments are exogenous and there is no particular benefit from the recovery of payments through sanctions, the problem could be represented as the maximisation of non-weighted compliance, subject to a budget constraint and taking into account farmers' optimal solution.

Assuming a given frequency of each farm type in hectares (λ_i), a total budget *B*, and a cost per hectare of monitored land km_i, where *k* is the cost of 100% monitoring, we can write the public decision making problem as:

$$\text{Max} \sum_i \lambda_i e_i \tag{5}$$

s.t. (3) and:

$$\sum_i \lambda_i k m_i \leq B \tag{6}$$

This representation appears realistic enough for the case of Italy and simple enough to be easily tractable both in the derivation of the theoretical solution and for computational purposes.

Based on 4, we can rewrite 5 as:

$$\text{Max} \sum_i \lambda_i f_i\left(m_i \rho P_i\right) \tag{5'}$$

Taking the Lagrangian this yields:

$$\sum_i \lambda_i f_i\left(m_i \rho P_i\right) - \gamma\left(\sum_i \lambda_i k m_i - B\right) \tag{7}$$

Optimisation (first derivative equalled to zero) with respect to the degree of monitoring yields, after some arrangements:

$$f_i'(m_i \rho P_i) = \frac{\gamma k}{\rho P_i} \quad (8)$$

Given the properties of $\Psi_i(e_i)$, $f_i'(m_i \rho P_i) \geq 0$.

Equation 9, says that, at the optimal level of monitoring the marginal increase in compliance with respect to cost equals the ratio between the marginal cost of monitoring and the marginal sanction for each farm. As increasing the monitoring effort the right hand side becomes lower, this means that the optimal amount of monitoring increases for low costs of monitoring and for low shadow cost of the budget constraint, while it decreases for higher sanctions. As the sanction is determined by ρP_i, both a higher percent of payment used as sanction and a higher payment contribute to lower optimal monitoring. In particular, as P_i is the only component of the right hand side of equation (9) which is differentiated by farm type, this implies that farms with higher payments other things equal should be monitored less.

This also means that for farms types with $P_i > 0$:

$$f_i'(m_i \rho P_i) P_i = \frac{\gamma k}{\rho} \quad (9)$$

will hold for all farms and $f_i'(m_i \rho P_i) P_i$ will be equal across farms at the optimum.

Farms with zero payments will have both compliance and optimal monitoring equal to zero.

The budget constraint may be expected to hold with equality for all cases with average $e < 1$. When this does not apply, i.e. there an excessive budget is available, $f_i'(m_i \rho P_i) = 0$ at the optimum.

The model presented here considers explicitly m_i amenable to be differentiated by farm type. This guarantees the maximum flexibility to the regulator, but may be not realistic in some cases. Reasons may derive from political opposition to differentiate controls (that could be seen as not equitable) or from technical problems. The latter is also connected to the way farm types are defined, and, in particular, the differentiation of m could be designed based on some characteristic *j* different from *i*.

In order to estimate the potential benefit from the targeting of controls, we simply consider the possibility of an uniform *m* across farms, i.e. all the farms have the same probability to be controlled. Substituting m to m_i in the previous formulation, optimisation from the point of view of the regulator yields:

$$\frac{\sum_i \lambda_i P_i f_i'(m \rho P_i)}{\sum_i \lambda_i} = \frac{\gamma k}{\rho} \quad (10)$$

Equation 10 says that the optimal solution already found in equation 9 holds here only on average, while it will not be possible for individual farm types. This is enough to grasp the fact that this solution yields a worst result for the regulator compared to a targeted m_i.

4. Case study

The methodology is applied to a case study represented by the province of Bologna (NUTS 3, Emilia Romagna, Italy). The province has been selected as it offers a range of different environmental conditions, farm structure and Single payment entitlements. It covers a UAA of 146 thousand ha. The province consists of 60 municipalities distributed on plain, hilly and mountain areas. The data used are based on the 2000 census. On the bases of the census structural data, farm types have been defined based on the average characteristics of each combination of municipality and farm size. This yields 600 farm types (60 municipalities by 10 classes of farm size). The payments assigned to every farm type are based on the crop mix and payments in place in the period 2000-2002.
Operationally the cost of compliance has been calculated as a quadratic function with the form $\Psi_i(e_i) = \varphi e_i^2$ and $\Psi_i'(e_i) = 2\varphi e_i$. As φ is considered as equal for all farms types, also $f_i'(m_i \rho P_i)$ will be a constant and the difference between farms will be only due to P_i. Differences in P_i may depend on three reasons: the different location, the different mix of eligible crops and the different ratio between eligible crops and non-eligible crops in the crop mix.
About the latest point, an important factor is that cross compliance applies to the whole farm, while the payments do not. As a result, the difference between farms is strictly connected to the difference in the share of area eligible for payments. In fact, the higher the area eligible for payments, the higher the payment/cost ratio connected to cross compliance.
To the knowledge of the authors, clear estimations of φ do not exist. Based on values reported in local literature (De Roest and Corradini, 2006), however, a reasonable range of such value has been identified between 10 and 40 euro/ha.
Based on European Commission (2007), the control cost has been calculated in the range 5-15 euro/ha. Given the level of uncertainty, the model has been used mainly to for paramerisation purposes. In particular, values have been generated for all combinations of the extreme values of the two variables listed above, three levels of sanction (ρ =0.1, 0.5, 1) and two levels of budget availability (B=20.000, 100.000) for the whole area.

5. Results

The results in the hypotheses of B= 20.000 euro show little relevant effects in terms of compliance (table 1).

Table 1. Results at the optimal monitoring level (B=20.000 euro, differentiated controls)

ρ	k	UAA controlled	φ	UAA compliant	
	euro/ha	%	euro/ha	ha	%
0.1	5	2.7%	10	5782	4%
			40	1459	1%
	15	0.9%	10	1997	1%
			40	506	0%
0.5	5	2.7%	10	24842	17%
			40	7156	5%
	15	0.9%	10	9341	6%
			40	2470	2%
1	5	2.7%	10	45209	31%
			40	13438	9%
	15	0.9%	10	17363	12%
			40	4838	3%

As the percent of area under farm types that receive no payment is only 4.6%, in all cases the vast majority of land will receive payments without complying with cross-compliance commitments. Actually only when the sanction can be high enough to equal the whole amount of the payments and the cost of monitoring is sufficiently low, some relevant amount of land is compliant (about 30%). This combination, however, is rather far from actual control effort and cost, so that the actual expected outcome would probably be closer to the first lines in the table, with likely effect close to zero. However, it should be clear that the amount of 20.000 euro is very low for the area, as it correspond to less than 0.2 euro/ha.

The controlled UAA is very small in percentage and only varies with *k*, as, due to the model structure, it is always preferable to use all the budget for controls till 100% compliance is achieved.

If a differentiated control is not possible, the results are sharply worse than in the previous case (Table 2).

Table 2. Results at the optimal monitoring level (B=20.000 euro, uniform controls)

ρ	k	UAA controlled	φ	UAA compliant	
	euro/ha	%	euro/ha	ha	%
0.1	5	2.7%	10	2977	2%
			40	744	1%
	15	0.9%	10	992	1%
			40	248	0%
0.5	5	2.7%	10	14886	10%
			40	3722	3%
	15	0.9%	10	4962	3%
			40	1241	1%
1	5	2.7%	10	29772	20%
			40	7443	5%
	15	0.9%	10	9924	7%
			40	2481	2%

The compliant UAA, in this case, is mostly around two thirds compared with the differentiated controls. This difference may be underestimated in the model as the choice of a uniform cost of compliance tend to reduce the variability of optimal monitoring compared to reality. Altogether this shows the importance of an improved targeting in order to improve value for money out of control activities.

The picture changes sharply when a more substantial budget for controls is assumed (table 3).

Table 3. Results at the optimal monitoring level (B=100.000 euro, differentiated controls)

ρ	k	UAA controlled	φ	UAA compliant	
	euro/ha	%	euro/ha	ha	%
0.1	5	13.7%	10	24842	17%
			40	6451	4%
	15	4.6%	10	9341	6%
			40	2397	2%
0.5	5	13.7%	10	92933	64%
			40	30158	21%
	15	4.6%	10	38693	26%
			40	11423	8%
1	5	13.7%	10	132388	91%
			40	54592	37%
	15	4.6%	10	69041	47%
			40	21158	14%

In this case, due to the much higher budget (5 times, but still below 1 euro/ha), the area under control increases substantially, however staying always below 14%. With this level of controls, the lowest levels of sanction are still connected to negligible amounts of compliance. However, for higher level of sanctions, it is possible to reach more than 90% compliance, when the cost of controls and the costs of compliance are assumed low. Actually, in the case of ρ =1, *k*=5 and φ =10, 13.7% monitoring is enough to reach almost the optimal level of compliance without budget constraint (93.5%). However, reaching such level would require an increase of monitoring to 18.2 of the UAA.

Again, the results are much worse in the case of uniform controls (Table 4).

Table 4. Results at the optimal monitoring level (B=100.000 euro, uniform controls)

ρ	k	UAA controlled	φ	UAA compliant	
	euro/ha	%	euro/ha	ha	%
0.1	5	13.7%	10	14886	10%
			40	3722	3%
	15	4.6%	10	4962	3%
			40	1241	1%
0.5	5	10.0%	10	54369	37%
		13.7%	40	18608	13%
	15	4.6%	10	24810	17%
			40	6203	4%
1	5	5.0%	10	54369	37%
		13.7%	40	37215	25%
	15	4.6%	10	49621	34%
			40	12405	8%

Noticeably, the differences are more important the higher is the area under control, with at least a couple of cases where the percent of compliant UAA falls well below half of the same case with differentiated controls.

6. Discussion

The results show that, in the present conditions of control and sanctions, only a small share of farms is interested in complying with cross-compliance. The profitability of the choice of compliance/non-compliance depends mainly on the amount of single farm payment entitlements compared with the cost, that are strictly related to total land available on the farm. These parameters, in turn, also depend on the peculiarity of each area (mountain/plain, protected/non protected).
An improvement may be obtained through a (costly) increase of control or sanctions, or through a better targeting of controls. The latter option, while interesting in terms of efficiency, opens the problem of an equitable treatment of different groups of farmers, as well as of the identification of clear priorities of territorial development of farming.
The main message, however, is that, in order to increase effectiveness, controls and environmental prescriptions themselves should be considered as a variable to be adapted to incentive compatibility criteria. This is somehow informally considered in the way regions plan actual cross-compliance and related control mechanisms. However, on a formal (regulatory) ground, there appear to be potential conflicts between incentive compatibility and property rights rationale to cross compliance design.
While the main points of compliance are caught by the model, it is clearly simplified with respect to the complexity of cross-compliance prescriptions, cost structure and the ability to detect non-compliance. Improvements may go in the direction of better specified compliance costs functions, possibly distinguishing the cost of single commitments and a better representation of differentiated farmers, for example in relation to their production specialisation. The environmental benefits of cross-compliance should be also considered, at least in relation to the combination of the location of different farms and of the commitments with which the farms are compliant.

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