Structural Agricultural Land Use Modeling for Spatial Agro-Environmental Policy Analysis

Carlo Fezzi and Ian J. Bateman

This paper develops a spatially disaggregated, structural econometric model of agricultural land use and production based on the joint multi-output technology representation introduced by Chambers and Just (1989). Starting from a flexible specification of the farm profit function, we derive land use allocation, input application, crop yield, and livestock intensity equations in a joint and theoretically consistent framework. To account for the presence of censored observations in micro-level data, the model is estimated as a system of two-limit Tobit equations via quasi-maximum likelihood. We present an empirical application using fine-scale spatial data covering the entirety of England and Wales and including the main economic, policy, and environmental drivers of land use change in the past forty years. A simulation of the effects of diffuse pollution reduction measures illustrates how our approach can be applied for agro-environmental policy appraisal.

Key words: agro-environmental policy, land use, multivariate Tobit, quasi-maximum likelihood, structural econometric modeling, system of censored equations.

JEL codes: C34, Q15, Q53.

The agricultural sector is an area of economic activity most subject to intervention, with policy objectives ranging from food security to biodiversity to the control of diffuse pollution. Farmers' land use decisions, whilst private, have often significant public implications, generating both external costs, such as wildlife-habitat changes, deforestation, and wetland degradation, and external benefits, like the provision of recreational opportunities. Encouraging agricultural land use change is, therefore, a commonly applied strategy for delivery of policy objectives, particularly in various areas of environmental management (European Commission 2000; Sumner, Alston, and Glauber 2010). Such decision making requires models of farmers' behavioral response that are well grounded in theory and are empirically sound, in order to quantify the impact of changes in policy, market conditions, and environmental factors on land use, production, and environmental externalities. These variables are inherently spatially heterogeneous, varying significantly over relatively small areas according to environmental, climatic, and socioeconomic conditions. For this reason, spatial data are increasingly incorporated into econometric land use models for applied agro-environmental policy analysis. This article presents a spatially explicit, structural econometric framework embracing land use decisions, crop and livestock production, input applications, and profits. The resulting model is then used to consider a current policy–relevant issue concerning interventions aimed at reducing agriculture's negative environmental externalities.

Various studies have developed spatially explicit, econometric models to explain crop allocation choices and their implication for the environment. Examples include research by Lichtenberg (1989), Wu and Segerson (1995), Chomitz and Gray (1996), Wu et al. (2004), Lubowski, Plantinga, and Stavins (2006), and Langpap, Hascic, and Wu (2008). Irwin et al. (2009) and Brady and Irwin (2011) present

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recent reviews. The studies most closely related to ours are by Arnade and Kelch (2007) and Lacroix and Thomas (2011). Like us, they build upon the dual multi-output profit function with fixed allocatable inputs introduced by Chambers and Just (1989) to derive land use allocations, input demand, and output supply equations in a unifying framework. However, there are some differences both in the theoretical models (particularly in the approaches used to derive land use equations) and in the empirical, econometric specifications. On the first point, Arnade and Kelch (2007) obtain estimable land use equations by setting the shadow price of land equal to the observed land prices, while Lacroix and Thomas (2011) find the optimal land allocations by computing the derivatives of the profit function with respect to the crop area subsidies. On the other hand, we remain closer to the original Chambers and Just (1989) development and derive land use share equations using the first-order conditions of the profit maximization problem.

Regarding the empirical specification, Arnade and Kelch (2007) illustrate their approach on aggregated data and, therefore, can ignore the presence of corner solutions in farmers' production decisions. However, both farm-level data and fine-scale spatial data are characterized by censored observations. Failure to adequately account for this feature produces biased and inconsistent parameter estimates (Amemiya 1973). We address this issue by showing how the land use share and the input and output equations derived from the joint profit function can be specified as a system of simultaneous Tobit equations (Tobin 1958). In doing so, we draw upon approaches recently developed for estimating censored household demand systems (e.g., Dong, Gould, and Kaiser 2004; Meyerhoefer, Ranney, and Sahn 2005; Yen, Lin, and Smallwood 2003). Likewise, Lacroix and Thomas (2011) tackle this problem by using a two-step estimation method, building on Wooldridge (1995). Their technique uses a fixed-effect estimator to control for unobserved heterogeneity among farmers, while we explicitly model differences in soils, climate, and other environmental, policy, and economic drives by using spatially disaggregated data.

To our knowledge, this article is the first implementation of the Chambers and Just (1989) approach into a spatially disaggregated model accounting for multiple sources of heterogeneity. The empirical application is based on a large panel of 2-km^2 grid records collected in each of the seventeen Agricultural Census years from 1969 to 2006 for the entirety of England and Wales (EW). This rich database allows us to capture the heterogeneity in EW topographic, soil, and climatic characteristics, alongside the corresponding variation in agricultural practices. While these data are ideal for investigations of the environmental impact of agricultural land use, the disadvantage of using such a detailed spatial resolution is that information on profits is not available at this fine a scale. Therefore, unlike Lacroix and Thomas (2011), we cannot estimate the entire structural model, but can still address those equations that deal with land use and livestock numbers: the two main determinants of farms' ecological footprint (e.g., Lord and Anthony 2000; Lord, Anthony, and Goodlass 2002, concerning diffuse nutrient pollution to rivers; Phetteplace, Johnson, and Seidl 2001, regarding greenhouse gas emissions). Since the main focus of this paper is to encompass the spatial heterogeneity of agricultural land use and its environmental implications within a structural framework, we conclude by presenting a policy-relevant application analyzing the impacts of spatially targeted diffuse pollution reduction measures, motivated by recent European Union (EU) directives (European Commission 2000).

The Modeling Framework

The theoretical framework underpinning our structural model builds upon the Chambers and Just (1989) farm profit maximization problem in the presence of fixed allocatable inputs. The empirical model is then derived by specifying the profit function as a normalized quadratic.

The Theoretical Model

Consider a farm profit maximization problem with land as the only fixed allocatable input. Furthermore, indicate with $\mathbf{y}$ the vector of m outputs, with $\mathbf{r}$ the vector of n inputs, with $\mathbf{p}$ the vector of strictly positive *expected* output prices, with $\mathbf{w}$ the vector of strictly positive input prices, with $\mathbf{l}$ the vector of h land use allocations, with L the total land available, and with $\mathbf{z}$ the vector of k other fixed factors (which may include physical and environmental characteristics, policy incentives and constraints, etc.).[1] Note that input and output

[1] We consider *expected* output prices rather than observed prices because farmers formulate their land allocation and production

prices are farm-gate prices and, therefore, take into account transportation costs. Since we are also considering livestock outputs, we generalize the original framework allowing the number of possible land uses h to be different from the number of possible outputs m. In fact, while having each land use type producing a specific output is an acceptable depiction of arable systems, it generally misrepresents livestock farms, where a specific land use can be used for more than one output type (e.g., grassland can be used to raise both beef and dairy cattle).[2]

Given the fixed land allocation, the multi-output profit function can be written as:

$$(1)\quad \pi(\mathbf{p},\mathbf{w},\mathbf{z},l_1,\ldots,l_h) = \max\{\mathbf{p}'\mathbf{y}-\mathbf{w}'\mathbf{r}:\mathbf{y}\in Y(\mathbf{r},\mathbf{z},l_1,\ldots,l_h)\}$$

where $Y(\mathbf{r},\mathbf{z},l_1,\ldots,l_h)$ indicates the producible output set for a given land allocation.[3] This profit function is positively linearly homogeneous and convex in input and output prices. In such a framework, one can derive the profit maximizing input demand and output supply given a fixed land allocation via Hotelling's lemma (Chambers and Just 1989). Furthermore, the profit function associated with the optimal land allocation can be written as:

$$(2)\quad \pi(\mathbf{p},\mathbf{w},\mathbf{z},L) = \max_{l_1,\ldots,l_h}\left\{\pi(\mathbf{p},\mathbf{w},\mathbf{z},l_1,\ldots,l_h):\sum_{i=1}^{h} l_h = L\right\}.$$

The farm profit maximization problem can be expressed, without any loss of generality, in terms of profit maximization per unit of land. Indicating with $\mathbf{s}$ the h land use shares corresponding to the land use allocations l, and with $\pi^L(.)$ the profits per unit of land, we can rewrite the optimal land use allocation problem as:

$$(3)\quad \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \max_{s_1,\ldots,s_h}\left\{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,s_1,\ldots,s_h): \sum_{i=1}^{h} s_h = 1\right\}.$$

This expression, whilst written in terms of land use share and profit per area, is equivalent to equation (2) and does not assume constant returns to scale. In fact, profit per area is a function of L, and therefore the profit maximizing shares depend on the total land available. Since the profit-per-area function is positively linearly homogeneous and strictly convex in input and output prices, one can derive using Hotelling's lemma the output supply (y^L) and input demand (r^L) per area (hereafter we refer to these quantities as input and output *intensities*) as:

$$(4a)\quad y_i^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial p_i} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial p_i} \quad \text{and}$$

$$(4b)\quad r_j^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial w_j} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial w_j}$$

where the superscript on s indicates the optimal shares, i.e. the shares that satisfy equation (3). The equations describing the optimal land allocations can be derived by recognizing that land is allocated to different uses in order to equalize their marginal rent or shadow prices.[4] In terms of optimal land use shares this can be written as:

$$(5)\quad \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,s_1,\ldots,s_h)}{\partial s_1} = \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,s_1,\ldots,s_h)}{\partial s_i}, \quad \text{for } i=2,\ldots,h$$

decisions without knowing with certainty what the price of the outputs at harvest time will be.

[2] An alternative solution to model livestock farms would be to sub-divide a pasture field devoted to multiple animal types into smaller fields, each one devoted to a specific animal. For instance, consider a grassland field used for both beef cattle and sheep production. In theory, we could allocate it to two distinct land uses: "pasture for beef" and "pasture for sheep," allowing us to maintain a 1:1 relation between output and land use types. While theoretically interesting, this subdivision is impractical as it would require *a priori* knowledge of the production function for both sheep and beef in order to implement the allocation.

[3] This framework assumes that farmers are risk neutral. However, empirical analyses (e.g. Chavas and Holt 1990; Pope and Just 1991) show that farmers decisions may present some degree of risk aversion. The approach outlined in this paper is, however, flexible enough to allow departures from risk neutrality. These could be encompassed following, for instance, Coyle (1999) or Sckokai and Moro (2005).

[4] Even if corner solutions arise, this condition still holds for all land uses receiving a nonzero allocation (see Chambers and Just 1989).

which are the first-order conditions of equation (3). The linearity of these equations in the optimal land allocations, including the constraint that the sum of the shares needs to be equal to one, leads to a linear system of h equations in h unknowns, which can be solved to obtain the optimal land allocation as a function of $\mathbf{p}$, $\mathbf{w}$, $\mathbf{z}$, and L.[5] For empirical estimation, relations (4) and (5) can be translated into a unifying framework encompassing land use share allocation, input and output intensities, and profits by directly specifying the profit function per area as one of the flexible functional forms available in the literature (see e.g., Chambers 1988).[6]

The Empirical Specification

We specify the profits per area as a normalized quadratic (NQ) function. This functional form has been widely applied in agricultural economics for modeling joint (in input) multi-output production processes (Arnade and Kelch 2007; Guyomard, Baudry, and Carpentier 1996; Moore, Gollehon, and Carey 1994; Oude Lansink and Peerlings 1996; Sckokai and Moro 2005). Some of the desirable properties of the NQ profit function are that it is locally flexible and self-dual and its Hessian is a matrix of constants (i.e., convexity holds globally). Furthermore, it allows negative profits (losses) that cannot be included in other specifications, such as the translog. Defining with w_n the numeraire good, indicating with $\mathbf{x} = (\mathbf{p}/w_n, \mathbf{w}/w_n)$ the vector of normalized input and output (netput) prices and with $\mathbf{z}^* = (\mathbf{z}, L)$ the vector of fixed factors including policy and environmental drivers and the total land available L, the NQ profit function can be written as:

$$
(6) \quad \bar{\pi}^L = \alpha_0 + \sum_{i=1}^{m+n-1} \alpha_i x_i + \frac{1}{2} \sum_{i=1}^{m+n-1} \sum_{j=1}^{m+n-1} \times \alpha_{ij} x_i x_j + \sum_{i=1}^{h-1} \beta_i s_i + \frac{1}{2} \sum_{i=1}^{h-1} \sum_{j=1}^{h-1} \times \beta_{ij} s_i s_j + \sum_{i=1}^{k+1} \gamma_i z_i^* + \frac{1}{2} \sum_{i=1}^{k+1} \sum_{j=1}^{k+1} \times \gamma_{ij} z_i^* z_j^* + \sum_{i=1}^{m+n-1} \sum_{j=1}^{h-1} \delta_{ij} x_i s_j + \sum_{i=1}^{m+n-1} \sum_{j=1}^{k+1} \phi_{ij} x_i z_j^* + \sum_{i=1}^{h-1} \sum_{j=1}^{k+1} \varphi_{ij} s_i z_j^*
$$

where $\bar{\pi}^L = \pi^L / w_n$ is the normalized profit per unit of land. This profit function is linearly homogeneous by construction, and symmetry can be ensured by imposing $\alpha_{ij} = \alpha_{ji}$, $\beta_{ij} = \beta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$. Only $h-1$ land use shares appear in the profit function, since the last one can be computed by difference and it is therefore redundant. Input and output intensities can be derived as in equations (4a) and (4b). For instance, if x_i is a normalized output price, the corresponding output intensity can be written as:

$$
(7) \quad \frac{\partial \bar{\pi}^L}{\partial x_i} = y_i^L = \alpha_i + \sum_{j=1}^{m+n-1} \alpha_{ij} x_j + \sum_{j=1}^{h-1} \delta_{ij} s_j + \sum_{j=1}^{k+1} \phi_{ij} z_j^*
$$

which contains the same structural parameters as the profit function. Furthermore, optimal land use shares can be derived by solving the following system of $h-1$ equations:

$$
(8a) \quad \frac{\partial \bar{\pi}^L}{\partial s_1} = \beta_1 + \sum_{j=1}^{m+n-1} \delta_{1j} x_j + \sum_{j=1}^{h-1} \beta_{1j} s_j + \sum_{j=1}^{k+1} \varphi_{1j} z_j^* = \beta_i + \sum_{j=1}^{m+n-1} \delta_{ij} x_j + \sum_{j=1}^{h-1} \beta_{ij} s_j + \sum_{j=1}^{k+1} \varphi_{ij} z_j^* = \frac{\partial \bar{\pi}^L}{\partial s_i},
$$

[5] More precisely, these results are valid also if the equations are linear in a monotonic transformation of the optimal land use shares (e.g., the logarithm transformation). This is true if profit per area is specified as a quadratic function of this monotonic transformation, as in most established flexible functional forms such as the translog and normalized quadratic. However, prices and other fixed factors can enter the profit function and derived land allocation equations in any desired functional form.

[6] Clearly, apart from the role of output price expectations, the decision making process proposed by this model is essentially static. However, agricultural land use decisions are inherently dynamic. They need to take into account crop rotations, perennial crops, conversion costs and many other intertemporal aspects (e.g., Just 2000). Nevertheless, almost all spatially explicit econometric land use models are specified in a static framework (Chakir 2009; Chomitz and Gray 1995; Chomitz and Thomas 2003; Langpap, Hascic, and Wu 2008; Lubowski, Plantinga, and Stavins 2006; Wu et al. 2004) with only recent contributions beginning to address dynamic decision making (De Pinto and Nelson 2009). Extending the structural model presented in this paper to encompass dynamic decisions represents an important avenue for further research.

$$\text{(for } i = 2, \ldots, h-1),$$

$$\text{(8b)} \qquad \text{with } \sum_{j=1}^{h} s_j = 1.$$

This system contains $(h-1)$ $(m+n+k+h/2+1)$ structural parameters that are also included in the profit function. Solving the system for the optimal land use shares leads to h reduced form equations:

$$\text{(9)} \qquad s_i = \theta_i + \sum_{j=1}^{m+n-1} \theta_{ji} x_j + \sum_{j=1}^{k+1} \eta_{ji} z_j^*, \quad \text{for } i = 1, \ldots, h$$

with $\boldsymbol{\theta}$ and $\boldsymbol{\eta}$ being the vectors of the parameters to be estimated, which are nonlinear combinations of the structural parameters in equation (8). This reduced-form system contains $h(m+n+k+1)$ parameters and $m+n+k+1$ restrictions:

$$\sum_{i=1}^{h} \theta_i = 1$$

$$\sum_{i=1}^{h} \theta_{ji} = 0, \quad j = 1, \ldots, m+n-1$$

$$\sum_{i=1}^{h} \eta_{ji} = 0, \quad j = 1, \ldots, k+1$$

which need to be satisfied to ensure that the sum of the shares equals one. Note that this leaves only $(h-1)$ $(m+n+k+1)$ free reduced form parameters, which, if estimated alone, are not sufficient to recover all the structural parameters in equation (10). To identify all the structural parameters and to maximize efficiency, the systems in equations (7) and (9) can be jointly estimated with the profit function in equation (6). The next section illustrates the data and the econometric framework required for this implementation.

Implementation for Agro-Environmental Policy Assessment

The previous sections presented a generalized methodology to jointly analyze agricultural profits, land use, input, and output decision. The focus of the empirical application and the data availability will drive additional assumptions necessary to translate this framework into a structural econometric model and determine the corresponding estimation technique. In this section we consider the data requirements for spatially explicit agro-environmental policy evaluation and present the corresponding econometric methods.

Data Requirements

We consider three possible implementation strategies, each supported by a different data source: (a) aggregated data on a national or regional level, (b) farm-level data, (c) spatially disaggregate data.

Data aggregated on a national level or on large regions are easily accessible and, therefore, have regularly served as demonstrative examples for methodological advances in the field (e.g., Arnade and Kelch 2007; Ball et al. 1997; Chambers and Just 1988; Just 1974). Fitting our framework to this type of data obviously requires the assumption of constant returns to scale per unit of land, which can be incorporated into the empirical specification by simply dropping the term L in the vector of fixed factors $\mathbf{z}$. Considering estimation, an important advantage of these data is the absence of corner solutions, which considerably simplifies the approach. In such a case, the profit function in equation (6), the netput intensity in equation (7), and the land use share in equation (9) can be specified with additive, normal residuals. Under these premises, the system can be jointly estimated via maximum likelihood (ML), imposing symmetry restrictions and ensuring convexity in prices (e.g., Diewert and Wales 1987). Land use shares, however, must sum to one, and therefore their corresponding error terms must sum to zero, implying that the residual covariance matrix of the share system is singular. The solution is simply to drop one of the land use share equations, obtaining estimates that are invariant to which equation is dropped (Barten 1969). Despite being easily accessible and convenient for estimation, the validity of these data for agro-environmental policy development is, unfortunately, quite limited. In fact, aggregating over large areas conceals spatial variation, crucial in determining the pattern of land use and its impact on the environment.

Farm-level data have the advantage of allowing the direct analysis of the decision-making units. For this reason, these data are the most suited to study of farmers' behavioral choices.

Assumptions on constant returns to scale are not required in this framework. On the other hand, estimation is considerably complicated by the presence of corner solutions in production decisions, which creates a significant amount of censored observations in both the land use share and the netput intensity systems. In such a case, the practice of assuming normal disturbances and implementing ML leads to inconsistent estimates (Amemiya 1973). We discuss an alternative, consistent estimation technique for our model later on in this section. Farm databases are often very comprehensive, including information on revenues, costs, capital stocks, and land use allocations. However, for confidentiality reasons, the precise position of the farm is typically omitted, and only the region or the province where the farm is located is released. This results in environmental and climatic drivers being either omitted from farm-level studies (e.g., Henning and Henningsen 2007; Lacroix and Thomas 2011; Oude Lansink and Peerlings 1996) or represented rather crudely (e.g., Sckokai and Moro 2005). With the availability of detailed environmental characteristics on a farm scale, these data would be the most suitable for model estimation. This wealth of information, in fact, would allow the analysis of the entire structural framework comprising equations (6), (7), and (9). However, this would still not be sufficient for spatially sensitive policy studies, because scenario analyses would require predictions over large areas for which knowledge of all farm boundaries would be necessary. Given that this information is unlikely to be available, constant returns to scale or other simplifying assumptions would be required to extrapolate model findings beyond the estimation sample. While this is a feasible analytic strategy, its weakness lies in a mismatch in assumptions between the modeling estimation and modeling prediction strategies.

Spatially disaggregated data represent a convenient middle ground between aggregated and farm-level data. In this category we include data that are aggregated on a scale that is (*a*) small enough to capture the spatial variation in the environmental and climatic drivers of farmers' behavior and (*b*) proportionate with the scale of the decision-making unit. The first characteristic reflects the need to effectively encompass the heterogeneity in climatic and environmental factors that drives the economic and ecological consequences of land use change. The second requirement addresses the modeling assumption that each spatial unit is a decision-making unit.[7] As discussed, this is a necessary compromise in order to be able to produce spatially explicit policy analyses, even when the model is estimated on farm-level data. The advantage of this framework is that model estimation and model predictions are implemented under the same assumptions. The disadvantage is that profits data are typically unavailable at this spatial resolution, meaning that the entire structural framework cannot be estimated. Indeed, if the objective is to calculate welfare impacts, farm-level data are the best option. If, instead, the interest lies in capturing the spatial heterogeneity of agricultural land allocation behaviors so as to accurately assess their environmental impact, then spatially disaggregated data are probably the most suitable among those currently available to the applied researcher. Finally, if the size of the spatial units is commensurate with the farm scale, corner solutions will be present also in this type of data. As with farm-level data, therefore, the estimation technique needs to take into account the existence of censored observation in the output intensity and land use share equations.

Estimation with Micro-Level Data and Censored Observations

The technique presented in this section consistently estimates the farm model, accounting for the presence of censored observations typical of both farm-level and spatially disaggregated data. Netput values are censored from below at zero, while land use shares are bounded between zero and one and constrained to sum to one. In such a case, assuming normal disturbances and implementing ML leads to inconsistent estimates of the systems in equations (7) and (9) (Amemiya 1973). To address this issue, the land allocation system can be specified a multivariate Tobit model (Tobin 1958), in which the latent shares s_i^* are defined as in equation (9) plus additive normal residuals, and observed shares are: $s_i = 0$ if $s_i^* \leq 0$, $s_i = 1$ if $s_i^* \geq 1$ and $s_i = s_i^*$ otherwise. This framework can be interpreted by recalling that agricultural land is allocated to different uses according to their associated shadow prices. Therefore, in

[7] Of course, spatially disaggregated data are sometimes subject to mismatching problems, since the boundaries of the spatial units often do not correspond to those of the decision making units. In such case the assumption that each spatial unit is a decision making unit can be substituted with the more general assumption of constant returns to scale and land market equilibrium.

each grid square, censoring from below (above) implies that the corresponding land use shadow price is lower (higher) than those of alternative uses. One concern arising from this specification is that although the adding-up restriction holds for the latent equations, it is not satisfied for the observed shares. We address this issue following Pudney (1989), who suggests treating one of the shares as a residual category, defined by the identity $s_h = 1 - \sum_{j=1}^{h-1} s_j$ and estimating the remaining $h-1$ equations as a joint system. This approach has been already implemented in applied demand analysis for the estimation of censored systems of equations using household data (Yen and Huang 2002; Yen, Lin, and Smallwood 2003). Applied studies are typically characterized by the presence of a residual "other land" category encompassing a composite bundle of highly heterogeneous and marginal land uses, which provides an obvious choice for the unmodeled category.[8]

When there are more than three equations, the ML estimation of a Tobit system requires the evaluation of multiple Gaussian integrals, which is computationally very intensive. The recent literature on consumer demand system estimation has proposed various approaches to address this issue, including two-step estimation (Shonkwiler and Yen 1999), minimum distance estimation (Perali and Chavas 2000), simulated maximum likelihood (Yen and Huang 2002; Yen, Lin, and Smallwood 2003), maximum entropy (Dong, Gould, and Kaiser 2004), and generalized method of moments (Meyerhoefer, Ranney, and Sahn 2005). In this paper we follow the practical and computationally feasible solution proposed by Yen, Lin, and Smallwood (2003), who suggest approximating the multivariate Tobit with a sequence of bivariate models, deriving a consistent quasi-maximum likelihood (QML) estimator. Considering two equations i and j and observation t, indicating with $\mathbf{q_t} = [\mathbf{x_t}; \mathbf{z_t^*}]$ the vector of explanatory variables, with $\boldsymbol{\delta}_\mathbf{i}$ and $\boldsymbol{\delta}_\mathbf{j}$ the vectors of parameters to be estimated, and with $\sigma_{i,t}$ and $\sigma_{j,t}$ the residual standard errors of the latent variables and defining $e_{i,t} = (s_{i,t} - \boldsymbol{\delta}'_\mathbf{i}\mathbf{q_t})/\sigma_{i,t}$ and $e_{j,t} = (s_{j,t} - \boldsymbol{\delta}'_\mathbf{j}\mathbf{q_t})/\sigma_{j,t}$, then the likelihood of the bivariate Tobit model censored between 0 and 1 can be written as:

$$(10)\quad \begin{aligned} L_{i,j,t} &= [\Psi(e_{i,t}; e_{j,t}; \rho_{ij})]^{I(s_{i,t}=0; s_{j,t}=0)} \\ &\times [\sigma_{i,t}^{-1}\sigma_{j,t}^{-1}\psi(e_{i,t}; e_{j,t}; \rho_{ij})]^{I(0<s_{i,t}<1; 0<s_{j,t}<1)} \\ &\times [\Psi(-e_{i,t}; e_{j,t}; -\rho_{ij})]^{I(s_{i,t}=1; s_{j,t}=0)} \\ &\times [\Psi(e_{i,t}; -e_{j,t}; -\rho_{ij})]^{I(s_{i,t}=0; s_{j,t}=1)} \\ &\times [\sigma_{i,t}^{-1}\phi(e_{i,t})\Phi[(e_{j,t} - \rho_{ij}e_{i,t})/ \\ &\times (1-\rho_{ij}^2)^{0.5}]^{I(0<s_{i,t}<1; s_{j,t}<0)} \\ &\times [\sigma_{j,t}^{-1}\phi(e_{j,t})\Phi[(e_{i,t} - \rho_{ij}e_{j,t})/ \\ &\times (1-\rho_{ij}^2)^{0.5}]^{I(s_{i,t}<0; 0<s_{j,t}<1)} \end{aligned}$$

where $\phi(.)$ and $\Phi(.)$ indicate the density and the distribution function of the standard normal, $\psi(.;.;.)$ and $\Psi(.;.;)$ the density and the distribution function of the standard bivariate normal and where $I(.)$ is an indicator function assuming value 1 when the argument condition is satisfied and 0 otherwise. In Tobit specifications, unmodeled heteroskedasticity is a serious problem, causing all parameter estimates to be biased. This can be taken into account by allowing the standard errors to vary across observations as a function of a vector of exogenous variables $\boldsymbol{\nu}$ and a vector of parameters $\boldsymbol{\zeta}$. Specifically, for observation t and equation i:

$$(11)\quad \sigma_{j,t} = \exp(\boldsymbol{\zeta}_i'\boldsymbol{\nu}_{i,t}).$$

Considering the land use share system that excludes the hth land use share, the likelihood maximized by the QML estimator can be written as:

$$(12)\quad L = \prod_{t=1}^{T}\prod_{i=1}^{h-1}\prod_{j=i+1}^{h-1} L_{i,j,t}$$

where T is the total number of observations within the sample. This QML estimator is consistent and allows the estimation of cross-equation correlations and the imposition of cross-equation restrictions. However, since the quasi-likelihood is different from the likelihood of the true model, the parameter covariance matrix needs to be estimated using the robust procedure introduced by White (1982). The same QML approach can be implemented to estimate the netput system in equation (7) but clearly neither discarding one of the equations nor applying any censoring from above.

[8] The resulting parameter estimates are not invariant to which equation is dropped. This is not a significant problem in most land use analyses, since the exclusion of the "other land" category is the logical choice according to the land use shares definition. When parameter invariance is a crucial issue, other estimation techniques can be implemented (e.g., Dong, Gould, and Kaiser 2004; Meyerhoefer, Ranney, and Sahn 2005).

As shown previously, the land use shares in equation (9) are expressed in reduced form, their parameters being nonlinear combinations of the structural profit function parameters included in equation (8). Estimation of equation (9) alone does not provide enough free parameters to identify the parameters in equation (8). However, if data on netput intensities and profits are available, these equations can be jointly estimated to increase efficiency and recover all the structural parameters. Clearly, the appropriate symmetry and convexity restrictions need to be imposed in estimation.

An Empirical Application: Agricultural Land Use in England and Wales

Given the current policy concern regarding the environmental and spatial aspects of agricultural land use, in this empirical analysis we focus on the land use and livestock number equations while maintaining the model's structural foundation and its clear underpinning assumptions.[9] Given the lack of detailed spatial-resolution data on profits, however, we will not be able to estimate all the structural parameters of the profit function, but only those relating to the livestock outputs.

Data, Sources, and Descriptive Statistics

We employ a unique database that integrates multiple sources of information dating back to the late 1960s. The resulting data, collected on a 2-km^2 grid (400 ha), cover the entirety of EW and encompass, for the past forty years: (*a*) land use shares and livestock number, (*b*) environmental and climatic determinants, (*c*) input and output prices, (*d*) policy and other drivers. The different data sources are described in detail below.

Agricultural land use data. Data on agricultural land use hectares and livestock numbers, derived from the June Agricultural Census (JAC) on a 2-km^2 (400 ha) grid, are available online from EDINA (the Edinburgh University Data Library), which aggregates information collected by the Department of Environment, Food and Rural Affairs (DEFRA), and the Welsh Assembly. These data cover EW for seventeen unevenly spaced years between 1969 and 2006 (in years 2002, 2005, and 2006, only Welsh data are available). This yields roughly 38,000 grid-square records each year and a total of about 580,000 observations.

Regarding livestock numbers, we distinguish between dairy cattle, beef cattle, and sheep. Dairy cattle also include those heifers less than two years old that are not in milk production but are classified as being part of the dairy herd in the JAC statistics. All nondairy cattle are categorized as beef cattle. Turning to consider arable land use types, we explicitly model cereals (including wheat, barley, oats, etc.), oilseed rape, root crops (potatoes and sugar beet), temporary grassland (grass being sown every three to five years and typically part of an arable crop rotation), permanent grassland (grassland maintained perpetually without reseeding) and rough grazing. These six land use types together cover more than 88% of the total agricultural land within the country. We include the remaining 12% in the "other" land category encompassing horticulture, other arable crops, woodland on the farm, set-aside, bare, fallow, and all other land (ponds, paths, etc.). As described on the EDINA website (www.edina.ac.uk), grid-square land use estimates are derived from parish summaries or DEFRA estimates, taking into account potential land use capability. These statistics can sometimes overestimate or underestimate the amount of agricultural land within an area, since their collection is based on the location of the main farm house. For example, when a farm's agricultural land belongs to more than one parish, all the land use is assigned to that parish in which the main farm is registered.[10] For this reason the recorded areas of certain extensive land uses, in particular rough grazing and permanent grassland, can sometimes exceed the total amount of land within a grid square (400 ha). We correct this feature by rescaling the sum of the different agricultural land use areas assigned to each grid square to match with the total agricultural land derived from the Agricultural Land Classification (ALC) system published by DEFRA and the Welsh Assembly.[11] This

[9] In addition to agent's risk neutrality, already imposed to derive the theoretical model, the empirical application requires the following additional assumptions: (*a*) all farmers use the same technology, conditional on the environmental and other observed factors, (*b*) factor supply are perfectly elastic, (*c*) unobserved variables are uncorrelated with the regressors.

[10] For a more detailed description see http://edina.ac.uk/agcensus/agcen2.pdf (accessed 7 April 2009).

[11] This data is described in detail at http://www.defra.gov.uk/farm/environment/land-use/pdf/alcleaflet.pdf (accessed on the 7

Table 1. Descriptive Statistics: Land Uses (ha), and Livestock Numbers (heads) per 2-km Grid Square

	1969	1988	2004	Total			
	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\hat{s}(x)$	Min	Max
Cereals	87.8	94.6	76.4	83.0	77.4	0	347.2
Oilseed Rape	0.1	8.5	13.3	6.9	12.3	0	124.7
Root crops	10.1	9.5	7.5	9.1	18.7	0	186.8
Temporary grassland	41.1	28.8	22.6	29.3	28.7	0	349.5
Permanent grassland	116.7	115.6	112.7	113.0	97.0	0	400
Rough grazing	47.1	39.6	40.5	44.0	100	0	400
Other	22.8	26.6	45.7	37.8	45.6	0	400
Tot. land	325.6	323.2	318.7	323.1	96.9	1.25	400
Dairy	87.1	71.5	62.0	74.1	99.1	0	1128
Beef	151.4	149.8	89.9	144.9	123.8	0	1221
Sheep	472.2	784.1	323.8	693.6	899.0	0	11289

Notes: Only grid squares containing some agricultural land (according to the ALC) are considered; $\bar{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation.

rescaling process, while ensuring consistency, has no direct influence on model estimation, which is based on share data.

Descriptive statistics for the agricultural land use types and livestock numbers are reported in table 1 for three illustrative years and for the total dataset. These figures refer only to grid squares in which there is at least some land classified as agriculture according to the ALC. As shown in the table, whereas the total land devoted to farming has changed only slightly over the last forty years, its allocation between the different agricultural land uses has transformed considerably. In particular, the area of oilseed rape has increased substantially, driven by the soaring prices and the targeted support payments included in various reforms of the EU Common Agricultural Policy (CAP). In contrast, root crop shares have been decreasing somewhat, as their relative prices have fallen. However, because of their comparatively higher revenues, their cultivation continues to be limited primarilyby soil and climate factors. Cereals are consistently the main arable crops in the country, although changes in technology, prices, and area payments have induced variability in their area allocations. Temporary grassland has been steadily decreasing, whereas the areas devoted to rough grazing and permanent grassland have remained fairly constant. Land included in the category "other" has significantly increased, particularly since the 1990s, because of the introduction of set-aside and various grants encouraging farm woodland. In contrast, the last fifteen years have seen a decline of the livestock sector, with challenges such as the outbreak of bovine spongiform encephalopathy and decreasing prices leading to a considerable reduction in stocking rates. Finally, with concerns regarding the empirical specification in mind, it is important to note that all variables are obviously censored from below at zero, while the most extensive land uses (e.g., grassland) are also censored from above at the grid square size (400 ha).

Physical environment and climatic data. Using 2-km^2 grid data allows us to fully represent the heterogeneity that characterizes the UK farming system. For each grid square, we extract, from the National Soil Resources Institute Land Information System database[12]: average annual rainfall (denoted *aar*), autumn machinery working days (*mwd*, a measure of the suitability of the soil for arable cultivation), mean potential evapotranspiration (*pt*, indicating the amount of water that, if available, can be evaporated and transpired), median duration of field capacity (*fc*, reflecting water

April 2009). It is based on a series of surveys carried out from the late 1960s to the late 1980s and distinguishes agricultural land from urban and other non-agricultural lands. To account for urban area increases since the last survey, we augment this data using Land Cover Map 2000 information (Centre of Ecology and Hydrology, http://www.ceh.ac.uk/sections/seo/lcm2000_home.html, acc. 7 April 2009). However, in the United Kingdom the growth of urban areas has been relatively modest and the total amount of land devoted to agriculture has remained fairly constant over the last two decades (see DEFRA statistics at http://www.defra.gov.uk/environment/statistics/land/alltables.htm, acc. 7 April 2009). The reason for this static situation is that urban sprawl has been severely restricted in the UK by a series of urban planning policies dating back to the 70s (for a discussion see Couch and Karecha 2006).

[12] For more details, see http://www.landis.org.uk/gateway/ooi/intro.cfm (acc. 7 April 2009).

Table 2. Descriptive Statistics: Environmental and Climatic Determinants

	Units	$\bar{x}$	$\hat{s}(x)$	Min	Max
aar	mm	888.4	360.5	509	3980
mwd	days	53.0	37.2	0	143
pt	mm	507.8	52.3	240	608
fc	days	114.7	21.7	80	230
dd	°C	2290	169.2	1410	2641
alt	m	120.4	113.7	0	860
smore6	%	19.2	0.25	0	100

Notes: $\bar{x}$ indicates the sample mean; $\hat{s}(x)$ the sample standard deviation.

abundance in the soil), total number of degree days in the growing season (*dd*, from April to September), and mean elevation (*alt*). We also include the share of agricultural land with slope higher than 6 degrees (*smore6*) derived via geographic information system analysis from the Ordnance Survey, Digital Terrain Model.[13] Descriptive statistics, reported in table 2, highlight the significant spatial variability that characterizes these variables.

Agricultural inputs and outputs price data. The analysis requires detailed information regarding the main agricultural output and input prices during the past forty years. There is no unique source that supplies such a comprehensive database for the United Kingdom. Therefore, we compiled a new database by extracting time-series data from a variety of different sources, linked by data from common years. Cereals price is based on the simple average of wheat, barley, and oats prices, derived from DEFRA (2006), the Ministry of Agriculture, Fisheries and Food (MAFF; 1986), and Mitchell (1988). Root crops price is given by the average of potatoes and sugar beet prices, extracted from DEFRA (2006), MAFF (1986), and the Office of National Statistics (ONS; 1974–1985), the same sources being used for the oilseed rape price. Milk, dairy cows, beef meat (per cow), and lamb meat (per sheep) prices are based on DEFRA (2006) and ONS (1974–1985). Fertilizer price is derived from DEFRA (2006) and ONS (1974–1985); oil price from the British Petroleum Statistical Review of World Energy[14]; and milk quota (leased) prices from Ian Potter Associates (www.ipaquotas.com). Rather than using actual output prices in each year, we use expected output prices, defined as the predictions of an autoregressive model of order one, AR(1), with trend.[15]

Crop and livestock prices are farm-gate prices that also incorporate subsidies and levies, including arable area payments. Input prices are on a national level, whereas output prices are converted to a regional level using the agricultural output regional price statistics extracted from the UK Farm Business Survey for the years 1982–2000.[16] This regional variation reflects mainly differences in transportation costs. However, there can be additional variability in the distance to markets within cells belonging to the same region. To control for this feature, we specify netput prices to be a function of the distance to the closest "major market" (defined as a city with more than 200,000 inhabitants), *dist*, and of the size of the "local market," represented by the amount of urban area within the 2-km^2 grid cell, *s.urb*. Therefore, the farm-gate normalized price for netput i in cell c belonging to region r can be written as:

$$x_{i,c,r} = x_r + \lambda_{1,i} dist_{c,r} + \lambda_{2,i} s.urb_{c,r}. \tag{13}$$

To account for in-region variation in farm-gate prices, therefore, we substitute equation (13) into the livestock and land use share systems for each netput price. Note that in each equation the parameter relative to *dist* and *s.urb* will be linear combinations of the various values of $\lambda_{1,i}$ and $\lambda_{2,i} (i = 1, m + n - 1)$, and therefore those netput-specific "distance to markets" parameters will not be identifiable. However, the parameters of the regional prices x_rs will still be the structural parameters of the corresponding normalized prices.

Policy and other determinants. Policy changes, and in particular the several reforms that the CAP has undergone, have shaped the UK rural environment, underpinning significant changes in farming practices, cultivation, and livestock management. The

[13] For details see http://www.ordnancesurvey.co.uk/oswebsite/ (acc. 7 April 2009).

[14] See http://www.bp.com/productlanding.do?categoryId=6929&contentId=7044622 (acc. 7 April 2009).

[15] The choice of a single lag and trend is based on observing the partial autocorrelogram of the residual, which does not present evidence of unomodeled time correlation. Other approaches have been used to represent farmers' price expectations, examples of which are provided in Wu et al. (2004). Our strategy corresponds to that implemented by Wu and Segerson (1995), Oude Lansink and Peerlings (1996), and De Pinto and Nelson (2009).

[16] The Farm Business Survey (FBS) provides detailed information regarding the financial performance and physical and economic characteristics of UK farming enterprises. Its sampling covers more than 2,000 farms per year and is designed to inform policy decisions on matters affecting farm businesses and enable analysis of policy impacts. The main publication from the FBS data analysis is the annual report on Agriculture in the United Kingdom (DEFRA 2009).

subsidies directly linked to specific crop or livestock productions, such as the intervention prices, are already included in the output and input prices. In addition, we include both space-variable and space-invariant policy drivers. In the latter group we include the rate of compulsory set-aside and the milk (leased) quota price. In the former group we incorporate those area-specific policy measures that vary by both time and space. Specifically, we calculate the share of each grid square in each year which is designated as National Park, Nitrate Vulnerable Zone (NVZ) or Environmentally Sensitive Area (ESA).[17] NVZs, established in 1996 and extended in 2003 and 2008, have been designed to reduce surface and groundwater nitrate contamination in compliance with the EU Nitrate Directive (European Council 1991). The range of measures enforced in NVZs does not go beyond good agricultural practice, and therefore while being mandatory and uncompensated, these are not expected to significantly change agricultural land use shares. ESAs, introduced in 1987 and subject to various extensions in subsequent years, were launched to safeguard and enhance areas of particularly high landscape, wildlife, or historic value. Participation in ESA schemes is voluntary, and farmers receive monetary compensation for engaging in environmentally friendly farming practices, such as converting arable land to permanent grassland, establishing hedgerows, etc.

Estimation Results and Forecasting Performance

We implement the QML approach from equation (12) to estimate two censored, heteroskedastic Tobit systems: the three-livestock (dairy cattle, beef cattle, sheep) intensity system from equation (7) and the six land use (cereal, oilseed rape, root crops, temporary grassland, permanent grassland, rough grazing) shares system from equation (9). Selecting as starting values the parameter estimates of univariate, heteroskedastic Tobit models and using the Newton–Raphson method as the maximization algorithm, the QML approach converges in a convenient length of time for both systems.[18] We discard from the model the normalized price parameters that present a high collinearity (but always retain the own price and fertilizer price) to improve the estimates of the remaining ones, since the agricultural price variables in our sample, as in most studies, are characterized by a high degree of correlation.[19]

We do not estimate the model on the entire sample of about 580,000 observations because of computational reasons and concerns about possible spatial autocorrelation in the residuals. In our framework, among the possible causes of residual spatial correlation are unobservable spatially correlated variables, spatial spillovers, and measurement errors due, for example, to spatial aggregation (Anselin 1988). Ignoring such issues within a censored regression may lead to biased and inconsistent parameter estimates. In order to decrease the computational burden and remove residual spatial autocorrelation, we estimate the model using only a fraction of the original data selected via spatial sampling (e.g., Carrión-Flores and Irwin 2004; Nelson and Hellerstein 1997). This is defined by randomly extracting one grid square and then sampling every fourth grid cell along both latitude and longitude axes (i.e., considering only the corner grids in a four by four square of cells), leaving a subsample of roughly 30,000 observations (about 5% of the original data). Following Carrión-Flores and Irwin (2004), we assess the robustness of our results by comparing the parameters' estimates obtained from this sample with those derived from alternative sampling methods: two different spatial sampling schemes (sampling the fifth and eighth grid square in both dimensions) and a random selection of 5% of the data in each year.[20] Since cell-specific omitted factors can be present in our data, we allow the residuals to be correlated among observations pertaining

[17] Digital boundaries at a field level for National Parks, NVZs and ESAs in each year have been downloaded from MAGIC (www.magic.gov.uk).

[18] We estimate the model using the ml function in Stata 10.1 running on a 1.86 GHz Intel Core 2 Duo processor, with 2GB RAM. The six-equation land use shares system converges in just over six hours, whereas the three-equation livestock system requires only ten minutes.

[19] Despite the high-correlations, the price coefficients appear to be fairly stable across specifications: there is no change in significance or sign of any of the retained price parameters when the prices of the other outputs are included in the equations (the only exception is the parameter on fertilizer price in the permanent grassland equation, which changes from insignificant to slightly significant, but remains very low in magnitude).

[20] Recalling the discussion of the previous subsection, in all the sampling schemes we classify as outliers (and exclude from the estimation samples) those grid cells in which the JAC rescaling process would be too substantial. We define such cases as those in which: (*a*) the difference between the sum of the agricultural land use areas from the JAC and the total agricultural area according to the ALC is higher than the total grid cell size of 400 ha or (*b*) the ratio of these two agricultural areas is greater than 4 or smaller than 1/4. This roughly corresponds to 7% of the observations.

Table 3. Z-Tests of Parameter Invariance

		Land Use Share System (363 parameters)			Livestock Intensity System (198 parameters)		
Sample	N	% Reject	Max	Mean	% Reject	Max	Mean
A	19085	3.5	2.56	0.72	1.5	2.66	0.73
B	7539	1.7	2.73	0.61	2.0	2.18	0.67
C	29890	11.0	6.38	0.91	1.0	2.19	0.63

Notes: The z-tests assess the null hypothesis that all the parameters are not significantly different from those estimated using the base sampling scheme: randomly sample one cell and then keep one cell every four in both latitude and longitude axes (total number of observations = 29,860). Sample A = like the base scheme, but keeping one cell every five; sample B = like the base scheme, but keeping one cell in every eight. In those sampling schemes, the sampled cells are the same in every year. Sample C = randomly sample 5% of the cells in each year. Since the samples are drawn independently, indicating with β_X the parameter and with $V_{\beta X}$ the covariance matrix in sample X, the test is: $z = (\beta_A - \beta_X)/[V_{\beta A} + V_{\beta X}]^{1/2}$, which is asymptotically distributed as a standard normal. These are the same tests reported in Carrión-Flores and Irwin (2004). "% reject" indicates the percentage of times the test is rejected at the 95% level, "max" indicates the maximum value of the z-test, and "mean" the average value (both in absolute values).

to the same grid square in different years for the parameters' covariance matrix calculation (Williams 2000). Table 3 reports the summary statistics of the z-tests used to assess the null hypothesis that the models' coefficients estimated on the alternative samples do not differ from those estimated on the first sampling scheme. For both alternative spatial schemes (A and B), the percentage of significantly different coefficients at the 5% level is around 2%, which is less than half of the significance level, suggesting that no systematic difference arises from the choice of the sampling approach. In addition, the magnitudes of the highest z-tests are fairly low and compatible with the null hypotheses, given the large amount of parameters in both systems. Therefore, we do not find evidence of significant variation in parameters and can be reasonably confident of the estimates' robustness to the sampling scheme. The only exception is the random sampling approach (scheme C), which, according to our results, leads to some significantly different parameter estimates in the land use system (11% of the total). This can be due to the presence of spatial autocorrelation, which this approach is not designed to remove.

Table 4 reports the final parameter estimates of the land use share equations obtained with the first sampling scheme (i.e., every fourth cell selected across both axes). The sign and magnitude of the coefficients are consistent with our expectations. In particular, focusing on the economic determinants, in the upper part of the table, the own output-price effects are always positive and the cross-price effects negative. Considering potential policies to address diffuse pollution, an increase in fertilizer price decreases the optimal shares of nutrient-intensive crops, in particular oilseed rape and cereals, which are converted into more extensive land uses such as temporary grassland and rough grazing. Considering other policy drivers, as expected, significant conversion out of arable land follows an increase in the rate of set-aside. Similarly, ESA payments encourage significant switching from arable land to extensive grassland types (permanent grassland and rough grazing) but are typically not high enough to foster conversion of root crops, which is the most profitable crop in EW. Within National Parks, the optimal shares devoted to arable land and to grassland receiving fertilizer applications are also reduced, being replaced by land in the "other" category (e.g., woodland) and rough grazing. Considering the environmental determinants of land use, reported in the lower part of the table, favorable conditions for crop growth (e.g., more machinery working days, flatter land) increase the share of arable land, in particular of root crops. However, effects are highly nonlinear, as highlighted in figure 1, which represents the relationship between the land use shares predicted by our model and machinery working days, with all other variables held constant at their 2004 sample mean values. The nonlinear effects are particularly noticeable for the cereals share, which peaks at around 120 *mwd* and then slowly declines, being replaced by more profitable crops, such as potatoes and sugar beet. Finally, the parameters of the variance equations (not reported in table 4 to preserve space) are highly significant, suggesting a heteroskedastic residual component, which, if ignored, would have biased parameter estimates.

The estimated coefficients of the livestock intensity equations are reported in table 5.[21]

[21] Note that in the livestock equations the land use shares are modelled as exogenous, assuming that farmers maximize profits

Table 4. Land Use Share Equations Parameter Estimates

	Cereals	Oilseed Rape	Root Crops	Temp. Grassland	Perm. Grassland	Rough Grazing
$P_{cereals}$	0.132***	–	–	−0.047**	–	–
P_{rape}	–	0.148****	–	–	–	–
$P_{rootcrops}$	–	–	0.037*	–	–	–
$P_{fertilizer}$	−0.110***	−0.284****	−0.023*	0.069***	−0.018	0.035***
Set-aside rate	−0.425****	−0.116****	0.004	−0.010	−0.033	−0.025**
ESA share	−0.033***	−0.005	−0.001	0.001	0.039**	0.030**
Park share	−0.020*	−0.004	−0.003*	−0.018*	−0.062*	0.042*
Urban share	−0.056**	−0.018**	−0.004	−0.011*	0.082***	0.001
Distance to major city	−0.002	−0.016****	0.003	−0.010**	−0.036***	0.008*
smore6	−0.087***	−0.019***	−0.004	−0.006	0.128***	0.052****
alt	13.961***	3.027**	−3.466***	−1.072	#	#
alt^2	6.288**	1.672*	−1.070*	−0.745	#	#
alt <200 m	#	#	#	#	−0.068***	0.007
alt >200 m	#	#	#	#	0.084	−0.154*
I(alt >200 m)	#	#	#	#	−26.791	21.956
mwd	4.170****	0.332	1.575****	1.107***	−7.832**	−0.751
mwd^2	−1.303	−0.425	0.677**	0.152	−1.229	0.262
pt	6.625*	1.011	0.217	−3.582*	−25.853**	13.096**
pt^2	−2.749	−1.047	0.484	3.845*	5.663	−7.614**
fc	−4.807	−8.274**	−1.742**	0.942	6.432	5.164
fc^2	17.188**	−6.514*	2.568**	−6.479*	−21.100*	4.998
dd	−4.312	0.436	−4.767***	3.562**	34.183***	−6.103*
dd^2	2.540	0.269	1.646**	−1.375	−2.279	−1.370
aar	−3.193	−9.643***	5.128****	5.655**	0.137	7.930
aar^2	−1.055	−6.777**	1.612**	4.688**	−4.474	6.981*
Trend	0.0156	0.284****	−0.018***	−0.153****	−0.103***	0.044***
Const	41.276***	−13.65***	5.492****	16.550***	40.583**	−1.609

Notes: To preserve space the residual correlations, the parameters corresponding to the variance equations and those of the environmental factors interactions are not reported in the table, but are available under request from the authors. Environmental determinants included as orthogonal polynomials to eliminate correlation between the linear and the quadratic terms. – = variable removed because of collinearity with the other prices, # = parameter not included in the equation, * = *t*-stat >2, ** = t-stat >3, *** = t-stat >4, **** = *t*-stat >10. All variables defined as in table 1. N = 29,860.

These parameters are structural, in the sense that they are the same ones appearing in the profit function. The exceptions are the constant terms, which cannot be identified as the α_is appearing in equation (6), since they also capture the average impacts of all the possible omitted factors. Of course, profits data would not only allow this identification but also promote more efficient estimation of the remaining parameters.

in a two-step process and, therefore, treat land use allocations as fixed factors in the netput equations. This is the same approach employed by Arnade and Kelch (2007) and stems directly from the Chambers and Just (1989) profit function maximization. Using univariate Tobit models we empirically compare two estimation approaches: the standard ML which assumes that the land use shares are exogenous and a ML with instrumental variables to model land use shares as endogenous. The first strategy provides significantly superior out-of-sample performance for each of the three livestock equations. This suggests that, at least in our sample, land use allocation choices are planned on a longer-run basis and can be considered as fixed when evaluating livestock intensity decisions.

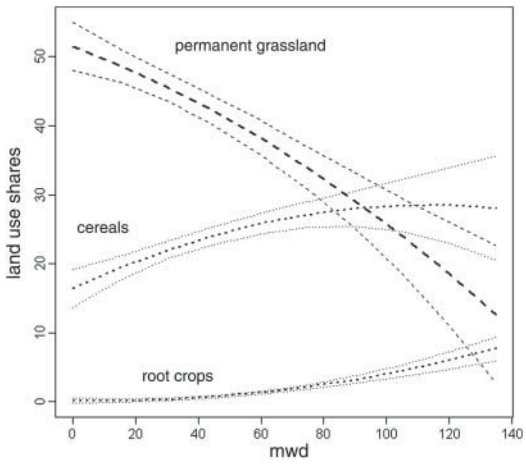

Figure 1. Relationships among predicted land use shares and machinery working days

Notes: Predicted shares and asymptotic 95% confidence intervals; all other explanatory variables fixed at their average levels in year 2004.

Table 5. Livestock Intensity Equations Parameter Estimates

	Dairy Cattle	Beef Cattle	Sheep
$s_{temp.grassland}$	1.427****	1.246****	1.926***
$s_{perm.grassland}$	0.438****	0.767****	2.455****
$s_{rough.grazing}$	0.041	0.294***	1.193***
P_{milk}	2.209***	–	–
P_{quota}	−3.041***	–	–
$P_{dairycows}$	0.004	–	–
$P_{beefmeat}$	–	0.086***	−0.208**
$P_{sheepmeat}$	–	−0.208**	3.279***
$P_{fertilizer}$	−0.262***	−0.309**	−1.118*
ESA share	−0.047**	−0.022*	0.065
NVZ share	−0.005	0.010	−0.146***
Park share	−0.009	−0.010	−0.307*
Urban share	0.026	0.168***	−0.400**
distance to major city	−0.003	0.028**	0.159**
smore6	−0.114**	−0.065*	0.982***
alt	−13.123**	0.405	−36.604
alt^2	−9.690	4.357	−12.419
mwd	−1.624**	0.566	−9.483
mwd^2	−2.117	−2.765**	−11.947*
pt	8.938	−21.386***	−64.743
pt^2	−1.347	25.989	0.785
fc	−5.006	−4.420*	114.733**
fc^2	−5.627	−13.089**	32.489
dd	−5.484	−13.125	−7.232
dd^2	−1.113	2.571	0.805
aar	6.253	−10.243*	−13.987
aar^2	3.939	0.340	65.543*
Trend	0.336***	0.385***	2.534***
$Trend_{BSE}$	−0.344***	−0.902****	−2.626***
Const	−18.719***	17.855*	8.504
$Dummy_{BSE}$	4.459**	10.64***	60.829***
$\rho_{i,j}$			
Dairy cattle	1		
Beef cattle	0.239****	1	
Sheep	−0.203****	0.182****	1

Notes: To preserve space the parameters corresponding to the variance equations and to the interactions of the environmental factors are not reported in the table, but are available under request from the authors. Environmental determinants included as orthogonal polynomials to eliminate correlation between the linear and the quadratic terms. – = variable removed because of collinearity with the other prices, * = *t*-stat >2, ** = *t*-stat >3, *** = *t*-stat >4, **** = *t*-stat >10. All variables defined as in Table 1. N = 29,860.

Considering the coefficients in table 5, own-price effects are always positive and significant, whereas cross-price effects, in particular between beef and sheep, are negative. Interestingly, the coefficient of milk quota price is significantly higher (in absolute value) than that of the expected milk price in the dairy cattle equation. This suggests the presence of significant transaction costs and uncertainties associated with the milk quota market (for a detailed analysis of the inefficiencies in the EU quota system, see e.g., Boots, Oude Lansink, and Peerlings 1997). Furthermore, each grassland type is associated with different optimal numbers of livestock. Again, model estimates confirm prior expectations: dairy cattle are reared primarily on intensive grasslands, beef enterprises are located on all types of pasture, and sheep are grazed mainly on less improved land, such as permanent grassland and rough grazing. In addition, an increase in the price of fertilizer, which is strongly related to grass growth and its consumption by animals, reduces the intensity of all the livestock enterprises considered. Also the share of land under special designation (NVZs, ESAs, National Parks, etc.) influences to some extent the average stocking density, both directly and by changing the proportions of land uses. Finally, the strong impact of the outbreak of bovine spongiform encephalopathy on the whole industry emerges in the estimates, with the trend in each livestock equation (particularly that for beef cattle) decreasing significantly after 1988.

Table 6. Forecasting Performance (MAE)

	MAE	$\hat{s}(x)$
Land use (*ha*)		
Cereals	24.5	71.2
Oilseed rape	8.4	17.9
Root crops	5.7	17.3
Temporary grassland	12.1	22.2
Permanent grassland	41.1	98.9
Rough grazing	19.1	98.3
Other	24.3	46.8
Livestock (*heads*)		
Dairy	47.0	92.1
Beef	61.3	119.6
Sheep	373.4	878.9

Notes: Mean absolute error (MAE) for England and Wales in year 2004. Total number of observations equal to 33,462 (outliers excluded).

Table 6 reports the mean absolute error (MAE) statistics for the land use share and the livestock equations calculated as the mean absolute value of the difference between the predictions and the actual JAC data, for the whole EW in 2004, this being the most recent year for which we have JAC data covering the entire country.[22]

Our approach is able to capture a significant proportion of the variability of the endogenous

[22] Since only 5% of the 2004 data are used to estimate the model, this consists of mainly out-of-sample forecasting. Therefore it is an appropriate yardstick to compare models performances avoiding the risk of preferring an over-fitted specification.

variables, with, for example, the MAE for cereals being about one-third of the standard deviation. The fit for the "other" category is somehow less satisfactory, since this class is not directly modeled, but it is estimated as a difference, as shown in equation (10). Finally, the MAEs for the livestock equations are adequate, considering that they are based on land use forecasts and not on actual values.

To highlight the spatial forecasting ability of our model, figure 2 maps actual (right-hand panel) and predicted (left) shares of cereals in 2004. The model performance is highly satisfactory, with the two maps showing essentially the same spatial pattern of land use. Some minor differences can be seen (e.g., in the south of England and in the West Midlands), and the actual data appear rather "blocky," with very high and very low values appearing immediately adjacent to each other. This is not likely to be a shortcoming of the model, but more probably is a limitation of the raw JAC data arising from the allocation of parish-level records to grid squares.

An Applied Policy Analysis: Quantifying the Effect of Diffuse Pollution Reduction Measures

The model illustrated in the previous sections covers all of EW and yet is based on a fine-scale data resolution capturing the spatial heterogeneity of both the physical environment and farmers' economic behavior. This section presents an application predicting land use changes and environmental impacts arising from a combination of measures aimed at reducing nutrient diffuse pollution from agriculture. This is a current policy focus, arising from the implementation of the EU Water Framework Directive (WFD). The Directive is the most substantial piece of EU water legislation to date, and it is designed to improve and integrate the way in which water bodies are managed throughout Europe. It requires EU member states to improve biodiversity in aquatic ecosystems and to achieve a "good ecological and chemical status" in all water bodies by 2015 (European Commission 2000). In EW, roughly 80% of rivers are currently at risk of not meeting these targets, with a major problem being diffuse nutrient pollution, which is dominated by agricultural sources (DEFRA 2004). Only in EW, the WFD implementation costs are foreseen to be higher than £300 million in net present value (DEFRA 2009). A variety of measures to reduce diffuse pollution from agriculture have been identified (e.g., DEFRA 2007; Fezzi et al. 2008, 2010), although to date their impact and effectiveness are still under investigation. This situation is further complicated by overlapping policy changes, such as

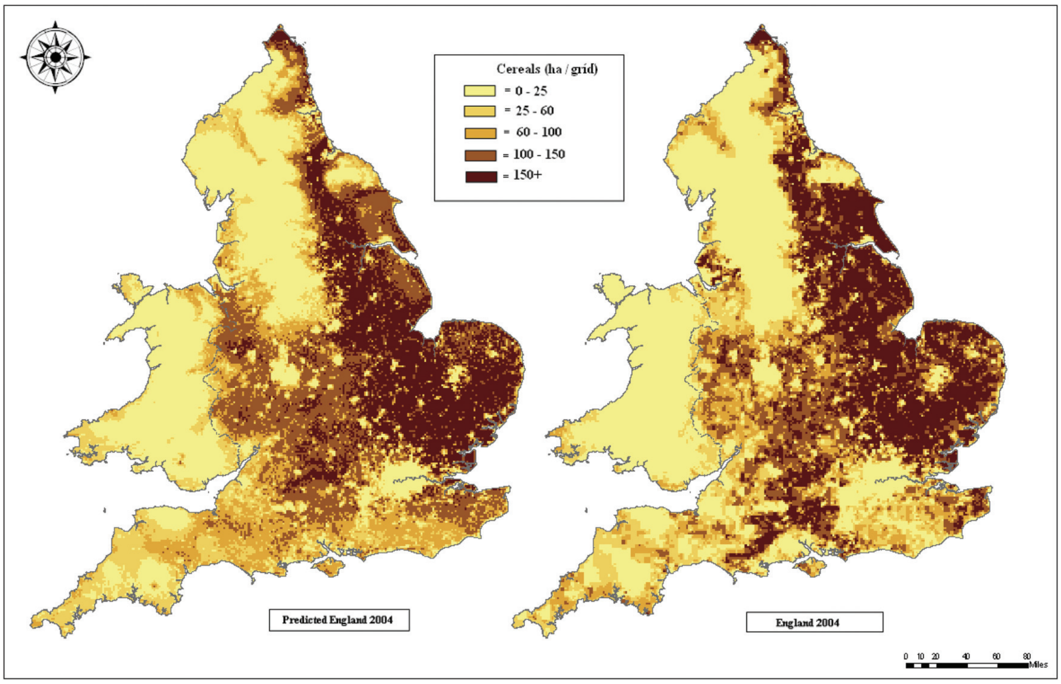

Figure 2. Cereals in 2004: JAC data and model predictions

the ongoing reform of the CAP, and external pressures, such as long-term shifts in food demand and climate change. Our approach includes, in a common framework, market, policy, and environmental drivers and therefore can be used to test complex scenarios, involving simultaneous changes of multiple factors. However, in order to isolate the effect of possible WFD implementation measures, we focus in this simulation solely upon nutrient reduction measures, holding all the other drivers stable at their baseline levels (year 2004).

To address the requirements of the WFD, a joint initiative by DEFRA, the Environmental Agency, and English Nature has identified forty catchments across England as priority areas for action and, via the Catchment Sensitive Farming Programme (CSFP), is providing both advice and direct payments aimed at influencing farming practices so as to reduce diffuse water pollution. In our simulation, we estimate the changes in land use and livestock numbers in these priority catchments arising from two possible nutrient leaching reduction measures: (*a*) a tax on fertilizer of £50/tonne, (*b*) designation of these areas as ESAs. We also address the implication of these two measures for diffuse pollution by calculating the corresponding changes in nitrogen (N) soil balance using the approach developed by Lord, Anthony, and Goodlass (2002).

Nutrient balance calculation is very transparent and relatively insensitive to variation in weather conditions, and it has been proposed as an indicator of agricultural diffuse pollution by various international organizations (e.g., the Organisation for Economic Co-operation and Development; OECD 2001). The approach is straightforward and consists of calculating the difference between the N inputs received by the soil (e.g., fertilizer, manure) and the consequent outputs (e.g., harvested matter removed from the field, including grass grazed by the livestock). Each agricultural activity, therefore, produces a nutrient surplus that is retained in the soil and will eventually leach to the water according to site-specific factors such as soil texture, slope, and rainfall. The N surplus indicates the nitrogen available for leaching from agriculture given a certain land use. In a relatively small country such as the UK, there is little variation in fertilizer inputs for a given crop, and therefore a single national set of surplus values for crops is appropriate (Lord, Anthony, and Goodlass 2002). Considering grassland, on the other hand, N application can change greatly, from roughly zero to more than 400 kg/ha, according to the livestock intensity. Therefore, adopting an N surplus per head of livestock approach is a more accurate representation of nutrient balance for this land use (Jarvis 2000; Lord, Anthony, and Goodlass 2002).

Results from our two scenarios are detailed in table 7. The first column reports estimates of the N surplus per hectare (or livestock head) per year arising from each agricultural activity (derived from tables 1 and 4 of Lord,

Table 7. Policy Simulation Results and Year 2004 Baseline (model and JAC data)

		JAC Rescaled Data	Model Predictions (changes in land use)		
	Annual N Surplus	Baseline	Baseline	£50 Fertilizer Tax	ESA Increase
	(Kg N ha^{-1})	*(10,000 ha)*	*(10,000 ha)*	*(%)*	*(%)*
Cereals	47.5	125.0	125.5	−0.9	−10.5
Oilseed rape	101.9	18.3	15.6	−15.0	−10.6
Root crops	65.8	16.1	10.3	−1.4	−2.9
Temp. grass	0	36.5	33.1	2.2	−1.5
Perm. grass	0	155.1	162.0	−0.1	10.0
Rough grazing	0	50.0	43.0	0.9	28.5
Other	25.6	82.2	93.6	2.9	−11.5
	(Kg N head^{-1})	*(10,000 heads)*	*(10,000 ha)*	*(%)*	*(%)*
Dairy	63.7	103.1	79.5	−1.9%	−11.5%
Beef	43.1	186.3	171.9	−1.5%	4.2%
Sheep	5.9	783.6	800.3	−1.4%	10.3%

Notes: Results refer only to grid squares included in priority Catchments Sensitive Farming areas. Nitrate surplus per year taken from Tables 1 and 4 in Lord, Anthony and Goodlass (2002). N surplus for "root crops" given by the average of sugar beet and potatoes, for "other" calculated by using the proportions of woodland, set aside, horticulture and other arable crops in year 2004 JAC. For dairy and beef cattle calculated by using the proportions of adult, followers and young cattle in year 2004 JAC. For sheep calculated by using the proportion of sheep and lambs in year 2004 JAC.

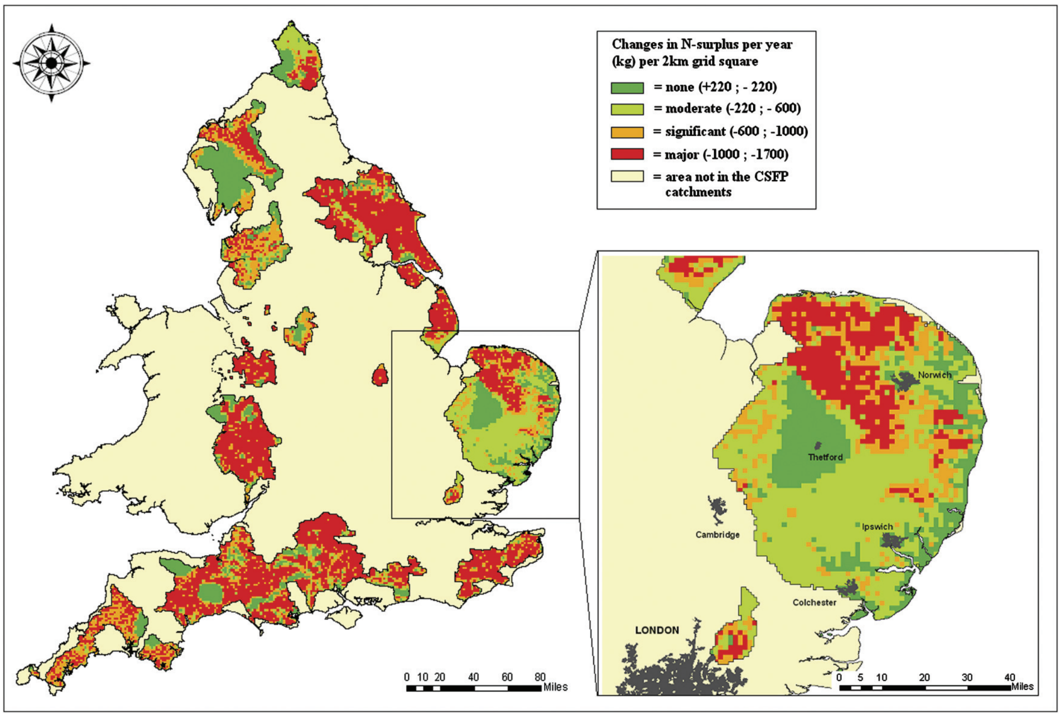

Figure 3. Changes in N-surplus per year (Kg per 2km grid square) arising from extending ESA regulation to all the CSFP priority catchments

Anthony, and Goodlass [2002]).[23] Subsequent columns report the total agricultural land use areas and livestock numbers in the CSFP priority catchments in 2004 according to the JAC and predicted by our model, and the percentage changes arising under each scenario. The predicted shares are very close to the actual ones. Considering the policy scenarios, a fertilizer tax of £50, apart from reducing quite significantly the shares of the most nitrate-intensive crop, oilseed rape, does not produce major land use changes, fostering some conversion from arable to temporary grassland and slightly decreasing livestock numbers, particularly dairy cattle. This is in line with the estimates by Lacroix and Thomas (2011), who show that only a very high fertilizer tax could reduce significantly N leaching. On the other hand, our model predicts important land use transformations arising from an extension of the ESA scheme to the priority catchments, with more than 120,000 hectares of arable land being replaced by permanent grassland and rough grazing. Considering the livestock sector, this policy significantly reduces the number of dairy cattle, which are substituted for less intensive units, such as beef cattle and particularly sheep.

To demonstrate the spatially sensitive nature of the model results, figure 3 shows predicted changes in diffuse pollution arising from extending ESA regulation to the CSFP priority catchments, produced by linking N surplus figures with the predicted changes in land use and livestock numbers. Even within the same catchment, policy impacts can be highly heterogeneous. For example, within the East of England (the magnified area of the map) the N surplus reductions vary from virtually zero (in the central afforested area around Thetford and on the coastline) to very significant (in particular in the northern area of the catchment, where intensive arable and dairy farming

[23] Rather than using a single value of N surplus for each crop and livestock type, a preferable approach would be to estimate a fertilizer intensity equation (which can be derived following the same strategy implemented for livestock numbers) and then calculate N surplus taking into account soil data. This is straightforward from a modelling perspective, since input intensities are already included in our framework, but cannot be implemented in this case-study due to a lack of the necessary, spatially disaggregated data on fertilizer applications. However, in the UK, fertilizer applications present little regional variation within crop (Lord, Anthony, and Goodlass 2002) and are rather inelastic to price (e.g., the British Survey of Fertilizer Practices 2006 reports only a 5% decrease in fertilizer applications to winter wheat from 2002 to 2006 despite a 40% increase in fertilizer price in the same period, with virtually no changes in wheat price).

are switched to more extensive agricultural land uses). On the national scale, variation is even more noteworthy, with major N surplus reductions typically taking place in the most agriculturally intensive areas.

Concluding Remarks

This article develops a structural approach encompassing agricultural land use decisions, livestock numbers, crop yields, input applications, and profits in a coherent and unifying framework. The underpinning theoretical model builds upon the joint multi-output profit function introduced by Chambers and Just (1989) and is translated into an empirically tractable system of equations by directly specifying the profit function as one of the flexible functional forms available in the literature. The system can be estimated on farm-level or spatially disaggregated data by implementing a strategy that is robust to the presence of censored observations. Here we propose an extension of the QML estimator developed by Yen, Lin, and Smallwood (2003) for systems of censored demand equations.

A large, spatially explicit, high-resolution database is compiled and used to empirically test this framework. The model is employed within a decision-relevant context to examine the impact of policy change using either input taxation or area-based schemes to reduce the incidence of diffuse agricultural pollution of water quality. Policy impacts are found to be highly spatially heterogeneous, and significantly affect margins that are both extensive (land use type) and intensive (livestock numbers). Given the key role that livestock play in nutrient leaching, this quantification is essential to assess environmental implications.

The findings of this research could be extended in several directions. First, while in the methodological section we propose a technique to estimate the entire profit function system, in the empirical application we did not recover all the structural parameters of the model and, therefore, did not derive the welfare implications of land use change. Farm-level data on profits and yields could be used to address this limitation and jointly estimate the entire system of equations (6), (7), and (9). The obvious drawback of this approach would be loss of the spatial dimension of the analysis, which could be at least partially maintained by knowing the locations of the farms and linking them to the environmental characteristics. Secondly, this model is general enough to be implemented in a variety of empirical contexts. Given the refined specification of the climatic variables, an obvious candidate is the prediction of the effects of global warming on agriculture. Finally, this framework is essentially static: an important extension would be to formulate a dynamic econometric specification to investigate the intertemporal aspects of agricultural production decisions.

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