The Dynamics of Farm Land Allocation –

Short and Long Run Reactions in a Long Micro Panel*

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Abstract

This study develops and estimates a dynamic multi-output model of farmers' land allocation decisions that allows for the gradual adjustment of allocations that can result from crop rotation practices and quasi-fixed capital constraints. Estimation is based on micro-panel data from Danish farmers that includes acreage, output and variable input utilisation at the crop level. Results indicate that there are substantial differences between the short-run and long-run land allocation behaviour of Danish farmers and that there are substantial differences in the time lags associated with different crops. To our knowledge, this is the first dynamic micro-model of land allocation estimated on data from the temperate climate zone. Since similar farming conditions are found in northern Europe and parts of the USA and Canada, this result may be of wider interest.

Key words: land allocation, crop rotation, system of dynamic equations, micro-panel data, GMM.

JEL classification: C33, Q12, Q15

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1. Introduction

Multi-crop farming involves managing cross-crop effects in a number of dimensions. Farmers often practice crop rotation reflecting positive and negative nutrient and disease/pest effects from the previous years' production decisions. In the Danish context, one example is that farmers typically take account of first year nitrogen carry-over effects in crop rotation schemes. Another example is that potatoes are not usually grown on the same plot for more than two consecutive years in order to reduce the risk of disease (e.g. potato blight) and pest attacks (e.g. potato stem borers). Following potato production, other 'cleaning' crops such as rape are produced for 3-4 years. Changing the land allocation often involves shifts between plots which are cultivated with different crop rotation schemes and the time delay before full implementation may be longer than a single rotation span.

Peak capacity constraints often generate other types of cross-crop effects. For example, Danish farmers typically prefer a mix of spring and winter crops of different types in order to spread sowing and harvesting seasons to reduce peak capacity utilisation of labour and equipment. Such cross-crop effects may in turn generate long and complex land allocation reaction delays if optimal cropping requires investment in new equipment. Rotation effects are made more complex since investments in machinery are often not made immediately, but at the time when it is optimal to scrap old depreciated equipment. Finally, harvest yields and output prices cannot be predicted exactly at the beginning of the growth season when the land allocation decision is made and must therefore be based on the farmer's expectations. Since expectations adjust to changes in underlying economic conditions, further delays in land allocation reactions may result.

Incorporating cross-crop linkages and dynamic adjustments makes for a challenging empirical problem when farmers' crop acreage allocation behaviour is to be estimated. Ideally, estimation should utilise a farm level dynamic setup which allows for adjustments in land allocation that incorporate cross-crop and equipment utilisation restrictions. However, in practice, the data required for the estimation of such a model (a long micro-panel with detailed information on crop level inputs, outputs and land allocation) are seldom available and thus other estimation strategies have typically been applied.

Empirical applications which use duality theory in connection with aggregate data are common and may give a reasonable indication of parameter magnitudes. For example, Guyomard, Baudry and Carpentier (1996) estimate crop acreage allocation response using aggregate annual time series, while Plantnga et al. (2002), Coyle (1993a), Coyle (1993b), Moore and Negri (1992), and Lichtenberg (1989) estimate land allocation using aggregate panel data. A number of papers using aggregated time series data have incorporated dynamic adjustment in one way or the other (see, e.g. Coyle (1993b), Howard and Shumway (1988) and Eckstein (1984) for nice examples and Askari and Commings (1977) for a comprehensive review of earlier studies). While results vary substantially between crops, countries and methods, many studies suggest the presence of sizable time lags.

Some studies use micro cross-section data at the farm level (e.g. Moore, Gollehon and Carey (1994); Mythili (1992); and Weaver and Lass (1989)) and estimation results are often interpreted as long run effects. Short-run adjustment effects have been estimated using micro-panels in a number of studies (e.g. Coxhead and Demeke (2004); Moro and Sckokai (1999); Lence and Hart (1997); and Lansink and Peerlings (1996)). However, these models do not attempt to estimate dynamic adjustment/inter-temporal effects. An exception is Thomas (2003), who estimates crop production functions and the nitrogen carry-over coefficients of different crops based on the assumption that farmers take account of nitrogen carry over and the potential for reducing future fertilisation costs that it entails. The estimated structural model allows for crop rotation schemes under the assumption that these are driven by farmers who take the dynamics of nitrogen carry over into account when maximising profit. The resulting structural model makes it possible to simulate the dynamic effects of various policies such as environmental policy aimed at reducing nitrogen loss where nitrogen carry-over is the dynamic effect of primary concern.

In this study, we develop and estimate a dynamic model of land allocation that takes account of a number of major causes of land allocation lags: expectations, adjustment costs, investment lags and crop rotations. Our model is based on farmers' dynamic optimisation behaviour and allows the estimation of land allocation conditional on expected crop gross margins. Our empirical estimation is based on a long micro-panel with up to 11 annual observations per farm and with detailed crop level data on acreage, output and variable input use, which makes it possible to calculate crop level gross margins. The ambition of addressing all major dynamic effects rules out the structural modelling of land allocation dynamics because of the unrealistic requirements for data and model complexity it would imply. Instead we estimate a reduced relationship between crop rotation, peak capacity effects and land allocation. Our empirical estimates are based on GMM methods (Arellano and Bond (1991) and Arellano and Bover (1995)) which are applied to a system of dynamic land allocation equations which takes the uncertain environment into account. To our knowledge, this is the first dynamic micro-model of land allocation under uncertainty to be estimated on data from the temperate climate zone that allows for crop rotation and other crop allocation lags.

We find substantial differences between short and long-run land allocation effects and also substantial variation in the adjustment speeds associated with different crops. For rape and pea, we find short-run land allocation elasticity with respect to its own per hectare gross margin in the order of 0.25, while the corresponding long run elasticity is in the order of 1.37. For winter crops such as barley and wheat, the corresponding elasticities are 1.00 and 2.08 respectively, and for spring barley 0.97 and 2.49 respectively. Time lags vary substantially between crops with first year effects ranging from about 20% (for rape) to 50% (for winter barley and wheat) of long-run effects. Since such estimates are absent in the literature, our results may be of interest in other European countries and parts of North America that produce under similar climatic and economic conditions[1].

[1] When comparing studies of farm land allocation across countries and continents, it is important to be aware that in addition to differences in climate and basic economic conditions, there may be important differences in the applied agricultural policies and environmental regulations.

In the next section, we present the economic model for the farmer's optimisation problem. In section 3, we describe the panel data set used in the estimation. In section 4, we derive the estimable equations and discuss the applied GMM estimators. The results are then presented in section 5, whilst section 6 concludes.

2. An Economic Model of Land Allocation

There is a large amount of literature on agricultural multi-crop production where there is an important dividing line between models that assume input jointness across outputs and models that assume non-jointness. The standard dual modelling approach is to model agricultural production as a multi-output production process, where input jointness is assumed across outputs, and to estimate a derived system of input demand and output supply functions (see, e.g. Heshmati and Kumbhakar (1994), Fontein et al. (1994) for applications to micro-panel data). Another line of work proposes a non-joint production function with fixed, but allocatable resources (e.g. land) providing the only form of jointness (see, e.g. Shumway (1988) and Moore, Gollehon and Carey (1994)).

Although the argument of non-jointness seems convincing for some inputs (e.g. fertiliser, pesticides, sowing seed, tractor fuel, etc.), true jointness seems probable for others (e.g. labour and capital). In a short-run model, one might argue that it is reasonable to treat capital and possibly labour as fixed inputs. However, because typically there are important peak utilisation capacity constraints around sowing and harvesting, jointness seems probable (i.e. if increasing production of crop 1 will require capital and labour in a peak period then production of other crops must be reduced).

In line with other studies we assume that inputs such as fertiliser, pesticides, sowing seed and tractor fuel are non-joint in the production of different crops (conditional on the allocation of cultivated land). Let the vector $\mathbf{\Omega}_j = \left(\mathbf{\Omega}_1, \mathbf{\Omega}_2, ..., \mathbf{\Omega}_j, .., \mathbf{\Omega}_J\right)$ be composed of J vectors with vector

$\boldsymbol{\Omega}_j$ indicating the amount of the different non-joint inputs allocated to the production of crop *j*. Let $\mathbf{Y} = \left(Y_1, Y_2, ..., Y_j, .., Y_J\right)$ denote the vector of crop outputs and $\boldsymbol{\Theta}$ a vector of stochastic variables capturing random variations in climate and disease/pest attacks and let L_j indicate the amount of land allocated to crop *j*. We assume the following production functions for the *J* crops:

$$Y_j = f_j\left(\frac{\boldsymbol{\Omega}_j}{L_j}, \boldsymbol{\Theta}\right)L_j \quad \text{for all j} \tag{1}$$

where crop production is homogenous in allocated land (L_j) and non-joint inputs ($\boldsymbol{\Omega}_j$). The land constraint is:

$$\sum_{j=1}^{J} L_j \leq L^{tot} \tag{2}$$

However, instead of letting jointness be generated through the land constraint alone, we assume true jointness for an aggregated indicator, *Z*, of quasi-fixed labour and capital inputs such as machinery in the production of 'cultivated' land for different crops. Let vector $\mathbf{L} = (L_1, L_2, ..., L_j, ...L_{J-1})$ denote the amount of cultivated land allocated to each of the first *J-1* crops and L^{tot} the total amount of land available.

We define:

$$0 = \widehat{F}(\mathbf{L}, L^{tot}, Z) \tag{3}$$

as the production frontier which describes the relationship between the vector of 'cultivated' land produced using available land and quasi-fixed labour and capital inputs.[2] Cultivating a given land area for different crops requires different levels and timings of capital and labour utilisation over the growing season, depending on when and how crops are sown, fertilised, sprayed with pesticides, harvested and stubbles ploughed. For example, combining winter and spring crops may require a lower level of available capital and labour capacity than if only spring crops are grown. Further, crop rotation schemes applied by farmers also imply restrictions on land substitution between crops. These constraints on the land allocated to different crops are captured in the $\widehat{F}(.)$ function which is assumed to be quasi-concave to ensure uniqueness so that the following relationship is implicitly defined by (3):

$$Z = F(\mathbf{L}, L^{tot}) \tag{4}$$

Given this, the farmer's long run maximisation problem becomes (assuming full adjustment of all quasi-fixed capital and labour inputs):

$$\begin{aligned} &\underset{L_1,\dots,L_J,\boldsymbol{\Omega}_1,\dots,\boldsymbol{\Omega}_J}{Max} \Pi = E\left[\sum_{\mathrm{j}=1}^{\mathrm{J}} \left[P^{Y_j} f_j(\boldsymbol{\Omega}_j / L_j, \boldsymbol{\Theta}) - \mathbf{P}^{\Omega}{}' \boldsymbol{\Omega}_j / L_j \right] L_j - P^Z F(\mathbf{L}, L^{tot}) \right] \\ &\text{s.t.} \quad L_J = L^{tot} - \sum_{j=1}^{J-1} L_j \end{aligned} \tag{5}$$

where P^Y, $\mathbf{P}^{\boldsymbol{\Omega}}$ and P^Z are the input-output prices, and expectations are taken over the joint distributions of $\boldsymbol{\Theta}$, P^Y, $\mathbf{P}^{\boldsymbol{\Omega}}$ and P^Z held by the farmer. This maximisation problem can be solved in two separate steps. The cultivation intensity problem is solved by deriving first order conditions for each non-joint input separately by differentiating the Lagrangian with respect to $\boldsymbol{\omega}_j = \dfrac{\boldsymbol{\Omega}_j}{L_j}$. Given the

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[2] Note that land allocation to crop J is given residually from (2) as $L_J = L^{tot} - \sum_{j=1}^{J-1} L_j$.

optimal combination of the non-joint inputs $\boldsymbol{\omega}_j^*$, we define the optimal per hectare expected gross margin $P_j^* = E_{\boldsymbol{\Theta},P^Y,\mathbf{P}^{\boldsymbol{\Omega}}}\left[P^{Y_j} f_j(\boldsymbol{\omega}_j^*,\boldsymbol{\Theta}) - \mathbf{P}^{\boldsymbol{\Omega}}{}'\boldsymbol{\omega}_j^*\right]$ and the expected capital/labour prices $P^{Z*} = E\left[P^Z\right]$. Assuming independence of the P^Z distribution and substituting in P_j^*, P^{Z*} and $L_J = L^{tot} - \sum_{j=1}^{J-1} L_j$, the land allocation problem becomes:

$$\underset{L_1,\dots,L_{J-1}}{Max}\ \Pi = P_J^* + \sum_{\text{j=1}}^{\text{J-1}} (P_j^* - P_J^*) L_j - P^{*Z} F(\mathbf{L}, L^{tot}) \tag{6}$$

Without loss of generality, this can be formulated in terms of land shares $\boldsymbol{l} = \mathbf{L}/L^{tot}$ and profit per unit land $\pi = \Pi / L^{tot}$ by defining the function[3]:

$$A(\boldsymbol{l}, L^{tot}) = F(\boldsymbol{l}L^{tot}, L^{tot}) / L^{tot} \tag{7}$$

By inserting (7) and dividing by L^{tot}, the farmers' long-run maximisation problem (6) is equivalent to choosing land shares so as to maximise profit per land unit:

$$\underset{l_1,\dots,l_{J-1}}{Max}\ \pi = P_J^* + \sum_{\text{j=1}}^{\text{J-1}} (P_j^* - P_J^*) l_j - P^{*Z} A(\boldsymbol{l}, L^{tot}) \tag{8}$$

Let $\boldsymbol{l}^*$ denote the solution vector to (8) (remembering that crop J is not included in $\boldsymbol{l}$ but is residually given by the land constraint). Farmers are able to adjust to $\boldsymbol{\omega}^*$ immediately from growing season to growing season, whereas adjustment toward $\boldsymbol{l}^*$ is only possible with a lag covering several growing seasons. Though the gross margins (P_j^*) and the capital/labour costs (P^{*Z}) that the farmer expects will apply in optimum are not observed in our data, we do observe realised land allocations, crop-specific realised gross margins and indicators of realised capital/labour costs.

[3] Note that $A(.)$ depends on L^{tot} because we do *not* want to assume homogeneity of $F(.)$ which would have ruled out scale effects.

Therefore, this formulation of the farmer's problem allows us to utilise the available data efficiently by focusing on the farmer's slow adjustment to the solution of the land allocation problem (8).

3. The data

The estimations are based on a panel data set provided by Landbrugets Rådgivningscenter (The Danish Agricultural Advisory Centre). The panel data set is unbalanced and covers twelve years (1980 to 1991) with, on average, 1,350 farms being represented each year.

Data are gathered through a voluntary programme which involves intensive consultations, which is run by the Danish Farm Associations Extension Service. Although it is not a random sample, participating farmers *a priori* are motivated and have an incentive to provide high quality data.

For each farm, data include detailed annual accounts of the variable costs for each crop (and for each branch of animal husbandry) along with corresponding accounts for quantitative flows of the most relevant inputs and outputs (e.g. fertiliser, pesticides, seed, crop yield, etc.). This allows us to calculate realised gross margins which are defined as income net of variable non-joint costs at the crop level. To avoid estimation intricacies of the handling of corner solutions (see, e.g. Weaver and Lass (1989)), we selected farms that produced all modelled crops for at least five consecutive years. To sustain a reasonable number of farms in the long panel, we base our model on three crop aggregates: (i) winter wheat, winter rye and winter barley; (ii) spring rape and pea; (iii) spring barley. The aggregates are chosen so that crops in the same aggregate hold the same position in the crop rotation systems typically used by Danish farmers. In addition to the required production, some of the selected farms also produce crops not included in the three groups, while others also produce pigs. For swine producers, pig production typically dominates value added and does not depend on the growth of fodder crops. Hence, the optimal level of pig production is probably not substantially influenced by land allocation decisions. Furthermore, a substantial part of land allocated to ‘other crops’ is used to grow sugar beets, potatoes and specialty crops typically on more lucrative long-range contracts. The existence of such contracts makes it less likely that optimal land allocation to ‘other crops’ will be substantially influenced by changes in the gross margins of the crops on which we focus. Thus, these production lines are not modelled, but they are included as conditioning variables.

Given these criteria, the data contain 226 farms in the selected panels covering 1980-1991 with 1,379 observations in total. The farms in the panel are observed for at least 5 and up to 11 years with more than half of the farms observed for 6 years or more (the structure of the panel is reported in table 1). Per hectare gross margins are calculated for each crop for each farm for each year as income from crops minus the following variable cost elements: pesticides, fertiliser, manure, phosphorus, calcium, sowing seed, energy for crop drying, tying string, machine station services and tractor fuel. We calculate single price indices for capital and labour services for each farm using the costs of labour and capital for each farm, as well as average farmhand wages and list prices for capital in Denmark.

Table 2 presents means and standard deviations for land shares, gross margins and other key variables. Note that total land on average amounts to 115.4 hectares, while less than 25 hectares are allocated to the other crops. Thus, farms included in the estimation utilise about 80 percent of the total land for crops covered by our model. Pig production averages 7.8 tons per farm. Figure 1 reports the average land shares, gross margins and capital and labour price index over time. Note that the average spring barley land share decreased until the mid-1980s, while the average land share of winter crops increased. During this period, the profitability of winter crops increased because of new pesticides which are more effective against pest/disease attacks. However, gross margins are also affected by variations in climate/weather conditions; in particular the large decreases in gross margins between 1985 and 1987 were primarily caused by low yields due to bad weather conditions in the growing and harvesting seasons.

4. Estimation

We estimate the farmers' second stage land allocation problem as formulated in (6). The model includes farms that, in addition to the three modelled crop aggregates, also grow other crops (mainly potatoes and sugar beets on long-term contracts) or have pig production. For these farms, land allocation is conditional on the level of these additional outputs. Thus, from (8) we have a single valued $A(.) = A(\boldsymbol{l}, L^{tot}, \boldsymbol{c}^*)$ where $\boldsymbol{c}^*$ is a vector of the two conditioning variables (pig production in tons and land cultivated with other crops in hectares) that the farmer expects will apply in long-run optimum.[4] This formulation also applies to core crop farms which are only growing the three crop groups (conditioning variables in this case have the value zero).

We assume a quadratic functional form for $A(\boldsymbol{l}, L^{tot}, \boldsymbol{c}^*) = \boldsymbol{l}'\boldsymbol{a} + \frac{1}{2}\boldsymbol{l}'\boldsymbol{A}'\boldsymbol{l} + \boldsymbol{l}'\tilde{\boldsymbol{a}}L^{tot} + \boldsymbol{l}'\tilde{\boldsymbol{A}}'\boldsymbol{c}^*$ so that the *J-1* first order conditions of the constrained maximisation problem in (8) become[5]:

$$\boldsymbol{l}^* = \boldsymbol{b} + \boldsymbol{B}\boldsymbol{p}^* + \tilde{\boldsymbol{b}}L^{tot} + \tilde{\boldsymbol{B}}\boldsymbol{c}^* \tag{9}$$

where $\boldsymbol{b} = \left[-\boldsymbol{A}^{-1}\boldsymbol{a}\right], \boldsymbol{B} = \left[-\boldsymbol{A}^{-1}\right], \tilde{\boldsymbol{b}} = \left[-\boldsymbol{A}^{-1}\tilde{\boldsymbol{a}}\right], \tilde{\boldsymbol{B}} = \left[-\boldsymbol{A}^{-1}\tilde{\boldsymbol{A}}'\right]$ and $\boldsymbol{p}^* = \begin{bmatrix}(P_1^* - P_3^*)/P^{*Z} \\ (P_2^* - P_3^*)/P^{*Z}\end{bmatrix}$ all vectors being 2x1 and matrices 2x2. Like $\boldsymbol{l}^*$ the $\boldsymbol{p}^*$-vector does not have an element corresponding to crop 3. $\boldsymbol{B}$ is symmetric (by the standard differentiability properties of the profit function and derived demands), homogeneity is maintained by normalisation so the eliminated crop 3 equation is obtained from residual calculation.

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[4] In the following, we use standard conventions for matrices, vectors and scalars, i.e. matrix names are always in bold capitals, vectors in bold non-capitals and scalars in non-bold.

[5] Differentiating (8) after inserting the quadratic functional form gives:

$$\begin{bmatrix}(P_1^* - P_3^*) \\ (P_2^* - P_3^*)\end{bmatrix} + \boldsymbol{P}^{*Z}(\boldsymbol{a} + \boldsymbol{A}'\boldsymbol{l} + \tilde{\boldsymbol{a}}L^{tot} + \tilde{\boldsymbol{A}}'\overline{\boldsymbol{C}}) = \boldsymbol{0} \Leftrightarrow$$
$$\boldsymbol{l} = \left[-\boldsymbol{A}^{-1}\boldsymbol{a}\right] + \left[-\boldsymbol{A}^{-1}\right]\boldsymbol{p}^* + \left[-\boldsymbol{A}^{-1}\tilde{\boldsymbol{a}}\right]L^{tot} + \left[-\boldsymbol{A}^{-1}\tilde{\boldsymbol{A}}'\right]\overline{\boldsymbol{C}}$$

Equation (9) defines long run optimal land allocation as a function of adjusted gross margins and conditioning variables expected by the farmer to apply in the long run. To allow for slow adjustment to the optimal land allocation $\boldsymbol{l}^*$ defined in (9), we assume a partial adjustment process, i.e.:

$$\boldsymbol{l}_t = \boldsymbol{l}_{t-1} + V(\boldsymbol{l}_t^* - \boldsymbol{l}_{t-1}) + \boldsymbol{e}_t \tag{10}$$

where $\boldsymbol{e}_t$ is a 2x1 vector of stochastic error terms and $\boldsymbol{V}$ is a 2x2 diagonal matrix of adjustment speed parameters with values between zero and 1.

At time *t*, the farmer holds an expectation of the vector of adjusted gross margins that will apply in the long-run optimum ($\boldsymbol{p}_t^*$ where *t* indicates that this is the expectation held by the farmer at time *t*). We assume that the current and previous year's realised adjusted gross margins in a linear combination is an unbiased (though uncertain) indicator of this expectation, i.e. that:

$$\boldsymbol{p}_t^* = \boldsymbol{D}\boldsymbol{p}_t + \bar{\boldsymbol{D}}\boldsymbol{p}_{t-1} + \boldsymbol{q}_t \tag{11}$$

where $\boldsymbol{p}_t$ is the vector of adjusted gross margins realised at time *t*, $\boldsymbol{D}$ and $\bar{\boldsymbol{D}}$ are 2x2 diagonal matrices of parameters where $\boldsymbol{D} = \boldsymbol{I} - \bar{\boldsymbol{D}}$ and $\boldsymbol{q}_t$ is a 2x1 vector of stochastic error terms. $\boldsymbol{p}_{t-1}$ is the latest observed adjusted gross margin when period *t* land allocations are decided at the beginning of the growing season and so the indicator allows for static expectations. The inclusion of $\boldsymbol{p}_t$ allows for some element of quasi-rational expectations or predictive ability (see, e.g. Burton and Love, 1996) since $\boldsymbol{p}_t$ is not observed at the time of land allocation (note that the $\boldsymbol{D}$ parameters are estimated and so $\bar{\boldsymbol{D}}$ may be zero). Given our data constraints, the assumed expectations model does not seem unduly restrictive.

At time t, the farmer also knows or predicts the vector of conditioning variables that will apply in the long-run optimum. Here, we again assume that the current and previous year's realised values in a linear combination is an unbiased (though uncertain) indicator of this prediction/expectation, i.e. that:

$$\boldsymbol{c}_t^* = \boldsymbol{G}\boldsymbol{c}_t + \bar{\boldsymbol{G}}\boldsymbol{c}_{t-1} + \boldsymbol{w}_t \tag{12}$$

where $\boldsymbol{c}_t$ is the vector of conditioning variables realised at time *t*, $\boldsymbol{G}$, $\bar{\boldsymbol{G}}$ are 2x2 diagonal matrices of parameters and $\boldsymbol{w}_t$ is a 2x1 vector stochastic error term. Equation (12) allows for the sluggish adjustment of optimal values of conditioning variables by letting the indicator depend on both their current level and growth rate.

Inserting (9), (11) and (12) in (10) gives the equation system to be estimated for each farm:

$$\boldsymbol{l}_t = [\boldsymbol{VBD}]\,\boldsymbol{p}_t + \left[\boldsymbol{VB}\bar{\boldsymbol{D}}\right]\boldsymbol{p}_{t-1} + \left[\boldsymbol{V}\tilde{\boldsymbol{b}}\right]L_t^{tot} + \left[\boldsymbol{V}\tilde{\boldsymbol{B}}\boldsymbol{G}\right]\boldsymbol{c}_t + \left[\boldsymbol{V}\tilde{\boldsymbol{B}}\bar{\boldsymbol{G}}\right]\boldsymbol{c}_{t-1} + [\boldsymbol{I} - \boldsymbol{V}]\,\boldsymbol{l}_{t-1} + \boldsymbol{u}_t \tag{13}$$

where $\boldsymbol{u}_t = [\boldsymbol{Vb}] + \boldsymbol{e}_t - \boldsymbol{VBq}_t - \boldsymbol{V}\tilde{\boldsymbol{B}}\boldsymbol{w}_t$ is a 2x1 vector of error terms and the square parentheses indicate the parameters to be estimated.

In estimation, there is a set of equations (13) for each farm in the panel. We allow the vector of constants $[\boldsymbol{Vb}]$ to be farm specific, while all other parameters are assumed to be common for all farms in the sample. However, a number of potential bias problems must be taken into account:

First, since we condition on interior solutions for at least 5 consecutive years, one might be concerned that this sample selection causes estimation bias. This does present a potential bias problem since, e.g. small farms (with only a few plots that are efficient to farm separately) and farms with a small optimal average land allocation to certain crops will have years with zero crop growth more often because of crop rotation rules. We do seem to have this type of a selection problem since mainly large farms are included in the analysis. Addressing this problem through a standard sample selection approach, such as Heckman (1979), would imply estimation of a vector of time invariant, but farm and crop-specific Mills ratios that should be added to the equations of (13). Controlling for unobserved time invariant heterogeneity in this way would ensure consistent estimates for the selected sample. Of course, the model would then only apply to the selected panel farms and not to the whole population of Danish farmers.

Second, the gross margin covariates $\boldsymbol{p}_t$ and $\boldsymbol{p}_{t-1}$ and the conditioning variables $\boldsymbol{c}_t$ and $\boldsymbol{c}_{t-1}$ are components of errored indicators and are therefore correlated with $\boldsymbol{u}_t$ requiring instrumentation.

Third, the inclusion of the lagged dependant variable in (13) may also cause estimation bias if error terms are serially correlated also requiring instrumentation.

To take account of these three potential bias problems efficiently, the unrestricted system (13) is estimated using the GMM-estimator suggested by Arellano and Bover (1995) and Blundell and Bond (1998). In the following, we refer to this estimator as the GMM-diflev estimator[6].

Even though the GMM-diflev estimator is derived for single equation models, it is easily generalised to handle multiple equation models exploiting the cross equation correlation to gain more efficiency. The standard econometric approach for linear dynamic panel data models is to first difference the equations to remove the unobserved permanent heterogeneity, which solves the first potential bias problem. Lagged levels of the covariates as instruments for the predetermined or endogenous covariates solve the second and third potential bias problems.

6 The estimator uses instruments in levels for first differenced endogenous variables and instruments in first differences for endogenous variables in levels.

The first and second lag may be correlated with the error components in first differences so we use earlier lags. Each instrument, m_{t-s}, for the covariates in the equations of (13) must satisfy the following two moment restrictions for the equation system in first differences of each farm:

$$E\left[\boldsymbol{m}_{t-s}\left(\boldsymbol{u}_t - \boldsymbol{u}_{t-1}\right)\right] = 0 \quad for \quad s \geq 3; \quad t = 4,5,...,T \tag{14}$$

In a conventional 2SLS framework, the instrument $\boldsymbol{m}_{t-s}$ can be the lagged levels of the covariates or the lagged differences of the covariates, similar to an approach suggested by Anderson and Hsiao (1982). However, we can increase efficiency by exploiting the additional moment restrictions that are given in equation (13), i.e. by also using lags earlier than the third as instruments and by using a weight matrix that takes into account that $\Delta\boldsymbol{u}_t$ follow MA(1)-processes, if $\boldsymbol{u}_t$ are i.i.d. or that $\boldsymbol{u}_t$ might be heteroscedastic. This can be achieved by the GMM estimator for single equations suggested by Arellano and Bover (1995) and so this estimator may be viewed as a system of equations, one for each year, where the number of instruments increases each year. Thus, in the equation for *t*=4, observations for *t*=1 may be used as instruments, while for *t*=5, observations for both *t*=1 and *t*=2 may be used.

Greater efficiency can be achieved by also using the equations in levels with lagged differences as instruments with the following two moment restrictions for the equation system in levels of each farm (see Arellano and Bover (1995) and Blundell and Bond (1998)):

$$E\left[\Delta\boldsymbol{m}_{t-s}\boldsymbol{u}_t\right] = 0 \;\; for \;\; s \geq 2; \quad t = 4,5,...,T \tag{15}$$

where $\Delta \boldsymbol{m}_{t-s}$ is the lagged first differences of a covariate, which may be used as an instrument. Note that since we only use instruments in first differences with the levels equations, we do not reintroduce selection bias caused by the omitted Mills ratios.

We use two types of weight matrices for the GMM estimators. One weight matrix takes account of the MA(1) structure of the first differenced disturbances and assumes no cross equation correlation and homoscedasticity. This estimator can be estimated in one step and is thus termed the one-step GMM estimator. The other weight matrix is consistent under heteroscedasticity and exploits all the cross-equation correlation both between disturbances of the same lag and between different lagged disturbances. This estimator uses the residuals from the one-step estimator to calculate the heteroscedasticity and cross-equation correlation consistent weight matrix after the same principle as in White (1980). The estimator is calculated in two steps and is thus termed the two-step GMM estimator. Even though the two-step GMM estimator in theory is more efficient, Monte Carlo studies by Arellano and Bond (1991) indicate that the one step estimate of the covariance matrix and thus statistical inference is more reliable, so we report results from both estimators.

As instruments for the equations in differences, we use the gross margins and the conditioning variables in third and higher lagged levels. Also, we use the land shares in third and higher lagged levels. For the equations in levels, we use these variables in second and higher lagged differences. Total land is instrumented with itself in both types of equations. As a general test of the validity (exogeneity) of the chosen set of instruments and lags, we apply the Sargan test of over-identifying restrictions for correlation between the residuals and the instruments (Arellano and Bond (1991)). We also test for second order serial correlation (termed M2) as a specific indicator of the validity of the chosen instrument lag structure (also see Arellano and Bond (1991)). If the M2 test provides evidence of second order serial correlation in the first differenced residuals, it indicates endogeneity of the third lag level in the difference equations and so, e.g. indicates that farmer expectations are based on earlier lags than assumed in our model. Finally, a specific check of the modelled dynamics (the important lagged dependent variable parameters) is possible by estimating indicators of the upper and lower bounds on the true parameter values. An indicator of the lower bounds emits from the within groups transformed model using the seemingly unrelated regression estimator, while treating all right-hand side variables as exogenous. This estimator is downward biased because the lagged dependent variable is negatively correlated with the error term. The lagged dependent variable parameter estimated in the dynamic model in levels is an indicator of the upper bound. This estimator is upwards biased because the lagged dependent variable is positively correlated with unobserved permanent heterogeneity that is dumped into the error term. However, in our case, the estimated bounds may also be affected by bias 'the wrong way' because of the measurement error components in the error term and so should not be interpreted rigorously.

A number of other tests and checks of the estimated model can be derived. We expect that the parameters to the crops own gross margin will be positive ($0 \le [\boldsymbol{VBD}]_{1,1}, 0 \le [\boldsymbol{VB\bar{D}}]_{1,1}, 0 \le [\boldsymbol{VBD}]_{2,2}, 0 \le [\boldsymbol{VB\bar{D}}]_{2,2}$ and that the parameters to the lagged land shares will be between 0 and 1 (i.e. $0 \le [\boldsymbol{I} - \boldsymbol{V}]_{1,1} \le 1, 0 \le [\boldsymbol{I} - \boldsymbol{V}]_{2,2} \le 1$). It is also clear from (13) that two common factor restrictions:

$$[\boldsymbol{VBD}]_{1,i} / [\boldsymbol{VB\bar{D}}]_{1,i} = [\boldsymbol{VBD}]_{2,i} / [\boldsymbol{VB\bar{D}}]_{2,i} \text{ for i=1,2} \quad (16)$$

should apply to the estimated system. Finally, the theoretical model implies symmetry of $\boldsymbol{B}$ which combined with the $\boldsymbol{D} = \boldsymbol{I} - \boldsymbol{\bar{D}}$ constraint emits the following restriction on the estimated parameters:

$$([\boldsymbol{VBD}]_{1,2} + [\boldsymbol{VB\bar{D}}]_{1,2}) / [\boldsymbol{I} - \boldsymbol{V}]_{1,1} = ([\boldsymbol{VBD}]_{2,1} + [\boldsymbol{VB\bar{D}}]_{2,1}) / [\boldsymbol{I} - \boldsymbol{V}]_{2,2} \quad (17)$$

which should also apply. The parameter restrictions (16) and (17) are implemented and tested using the Minimum Distance Estimator (e.g. Greene (2000)).

5. Results

In the first and second columns of table 3, we report parameters, standard errors, Sargan and M2 correlation tests of system (13) estimated without restrictions (16) and (17) using the one and two-step GMM estimator. The Sargan test of overidentifying restrictions is accepted and the M2 test statistic indicates no evidence of second order serial correlation. Therefore, the specification tests do not indicate endogeneity problems with the chosen set of instrument variables and lags. We see that the estimated parameters are almost equal for the two estimators and that many are significant. Specifically, parameters to the crops own gross margins are typically significant and with the expected sign. Some of the conditioning variable parameters are significant which indicates that the estimated system is inseparable from other farm production and that conditioning is necessary. Finally, both parameters to the lagged land shares (indicating the size of the adjustment time lag) are highly significant and within the required [0,1] bound. The winter crop parameter is also well within the estimated upper and lower bound indicators, while the corresponding rape parameter exceeds the upper bound slightly. However, the bound indicators are inaccurate in models with more than one measurement error and so this does not seem worrying[7].

Since the parameters emitted by the two estimators are almost identical, but inference from the one step estimator is more reliable (as noted above), we base our tests of restrictions on this model. The parameter estimates and restriction test when imposing common factor restrictions (16) and

[7] The estimated bounds on the parameter for the lagged winter crop land shares are [0.21;84] and the bounds on the rape and pea land shares are [1.6E-3;0.79].

when imposing both the common factor and the combined expectation and symmetry restriction (17) are reported in columns 3 and 4 of table 3, respectively. We see that both the common factor restrictions and the joint common factors and expectation and symmetry restrictions are accepted. Consistent with this, most of the significant estimates of the restricted models are similar to the corresponding estimates of the unrestricted model. In conclusion, the model seems well specified, soundly estimated and consistent with the underlying theory.

In table 4 columns 1 to 3, we present short and long run land allocation elasticities derived from the estimated parameters of the three models. Adjustment proportions ($1-[\boldsymbol{I}-\boldsymbol{V}]_{i,i}$) indicate the proportion of the long run land allocation effect implemented each year (e.g. if the adjustment proportion is 1 we have immediate adjustment to optimum). The short run elasticities are defined as $\sum_{j<3}(\frac{dl_{it}}{dp_{jt}}+\frac{dl_{it}}{dp_{jt-1}})\frac{dp_{jt}}{d(P_{qt}/P_{zt})}\frac{P_{qt}/P_{zt}}{l_{it}}=\sum_{j<3}([\boldsymbol{VBD}]_{i,j}+[\boldsymbol{VB\bar{D}}]_{i,j})\frac{dp_{jt}}{d(P_{qt}/P_{zt})}\frac{P_{qt}/P_{zt}}{l_{it}}$ for i=1,2 and q=1,2,3 reflecting the first year effect on land share i of a permanent increase in the gross margin of crop q[8]. The long run elasticity is found by dividing the short run elasticity by the adjustment proportion and this elasticity reflects the land allocation effect after full adjustment[9]. Elasticities are evaluated at the sample mean gross margins and land shares and the asymptotic standard errors are derived using the delta method.

[8] Note that by the definition of $\boldsymbol{p}^*$ below equation (5) $dp_{jt}/d(P_{qt}/P_{zt})$ equals 1 for (j,q)=(1,1) and (2,2), equals 0 for (j,q)=(1,2) and (2,1), and equals -1 for (j,q)=(1,3) and (2,3).

[9] For the numeraire crop, 3 short run elasticities with respect to gross margin q are calculated residually (using the land share adding up condition) as:

$$-\sum_{i<3}\sum_{j<3}(\frac{dl_{it}}{dp_{jt}}+\frac{dl_{it}}{dp_{jt-1}})\frac{dp_{jt}}{d(P_{qt}/P_{zt})}\frac{P_{qt}/P_{zt}}{l_{3t}} \Leftrightarrow -\sum_{i<3}\sum_{j<3}([\boldsymbol{VBD}]_{i,j}+[\boldsymbol{VB\bar{D}}]_{i,j})\frac{dp_{jt}}{d(P_{qt}/P_{zt})}\frac{P_{qt}/P_{zt}}{l_{3t}}$$

while the corresponding long run elasticity is $-\sum_{i<3}\sum_{j<3}\frac{[\boldsymbol{VBD}]_{i,j}+[\boldsymbol{VB\bar{D}}]_{i,j}}{1-[\boldsymbol{I}-\boldsymbol{V}]_{i,i}}\frac{dp_{jt}}{d(P_{qt}/P_{zt})}\frac{P_{qt}/P_{zt}}{l_{3t}}$. The average adjustment proportion for the numeraire crop can then be found by dividing the derived short run elasticity by the derived long run elasticity.

First, we note that the estimated adjustment proportions vary substantially between crops from 0.48 for winter crops to 0.18 for spring rape and peas. The difference between these estimates is highly significant with the constant time lags restriction $[\boldsymbol{I}-\boldsymbol{V}]_{1,1}=[\boldsymbol{I}-\boldsymbol{V}]_{2,2}$ being rejected strongly. The corresponding adjustment proportion for spring barley is 0.39.[10] Thus, the adjustments for winter crops and spring barley are slow and very slow for rape and pea. Overall this indicates that crop rotation and other restrictions make fast adjustment to changes in the current gross margins difficult.

The elasticities are almost equal across the models. All the own gross margin elasticities are significant across all the models with the exception of the long run own gross margin elasticity for rape and pea in the model with all restrictions imposed. For all models, the long run own gross margin winter crops elasticity is about 2 and the short run elasticity is about 1, while for spring barley it is of about the same magnitude (about 2.4 and 1.0). For rape and pea, the long run and short run elasticities exceed 2.3 and 0.4 in the unrestricted and common factor restricted models, while dropping by about 40% in the most restricted model. Thus, short run elasticities vary substantially between crops, while long run elasticities are more aligned.

Turning to the cross gross margin results, we see that most crops are substitutes. However, winter crops and rape and pea may be complements. Thus, the long run rape and pea elasticity, with respect to the winter crops gross margin, is 0.49 and the winter crops elasticity, with respect to the rape and pea gross margin, is 0.21 – both significant in the model with all restrictions imposed.

Figure 2 reports the development in the cumulated land share elasticity with respect to a permanent rise in the own gross margin at year 1. We see that, already in year 2, the cumulated elasticities deviate a lot from short run elasticities. By year 6, winter crops have almost fully adjusted. Adjustment for rape and pea takes in the order of 15-20 years.

[10] The estimate is derived from the short run and long run spring barley gross margin effects on the spring barley land share.

Since data limitations in some cases rule out the estimation of dynamic models, it may be of interest to compare the results from the dynamic model estimated here with a corresponding static model estimated on the same data set. We have estimated a static version of the model with instant adjustment to the optimal land allocation system (i.e. setting $[\boldsymbol{I}-\boldsymbol{V}]_{1,1}=0,[\boldsymbol{I}-\boldsymbol{V}]_{2,2}=0$). The estimated elasticities are reported in table 4, columns 4 to 6 and the parameter estimates are presented in the appendix (table A1). As expected, specification tests indicate misspecification (see column 2 of table A1). It is, however, notable that the gross margin short run elasticities in the static model are similar to the corresponding short run elasticities derived from the dynamic model (see table 4). Thus, even though misspecified, it seems that a static model is able to recover elasticity estimates that are close to the 'true' short run elasticities in our data set. In particular, this applies to the own gross margin elasticities. However, without knowledge of the adjustment lags that characterise the farmers in question, it may still be difficult to use these estimates for the evaluation of policy or price scenarios. This is illustrated in figure 2, where we see that cumulative land allocation elasticities after just 2-3 years differ by a factor 2 from the first year short run elasticities that may be recovered by a static model. Further, it is notable that because of differences in adjustment speeds, short run elasticities do not even give an accurate picture of ratios between crop elasticities after a few years. After 3 years, some ratios have changed by about a factor 2.

6. Conclusion

Using a long micro-panel with crop level data on acreage and gross margins, we estimated a dynamic model of land allocation that takes account of all the major causes of land allocation lags (expectations adjustment, investment lags and crop rotation because of pest/disease considerations and nutrient carry over). The identifying assumptions do not seem overly restrictive and the empirical model seems soundly estimated and consistent with the underlying theory.

We find substantial differences between short and long run land allocation effects and also substantial differences in the adjustment speeds estimated for different crops. For rape and pea, we find short run land allocation elasticity with respect to its own gross margin in the order of 0.25, while the corresponding long run elasticity is in the order of 1.4. For winter crops, such as barley and wheat, the corresponding elasticities are 1.0 and 2.1 respectively, while for spring barley they are 1.0 and 2.5 respectively. Time lags vary substantially between crops with first year effects ranging from 18% (for rape) to 48% (for winter barley and wheat) of long run effects.

This suggests that taking long run effects and time lags into account may be crucial when estimating and analysing policy effects on land allocation behaviour. It also suggests that even if a static model is able to recover short run (first year) elasticity estimates (as is the case in our data set – to some extent), such estimates should be used with great caution for policy and price scenario evaluations since cumulative elasticity levels and ratios changed substantially after just 2-3 years.

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Table 1a. Panel Structure

Years	Number of firms	Number of observations
5	103	515
6	53	318
7	38	266
8	15	120
9	11	99
10	5	50
11	1	11
	226	1379

Table 1b. Means and Standard Deviations

	Mean	std	min	max
Year	1985.26	2.77	1980.00	1991.00
Winter crop land share	0.42	0.18	0.01	0.87
Spring barley land share	0.39	0.17	0.04	0.92
Rape and pea land share	0.19	0.08	0.02	0.63
Winter crop gross margin	6714.04	2069.36	-27.14	12784.17
Spring barley gross margin	5433.12	1649.79	279.59	11457.22
Rape and pea gross margin	5977.28	2396.00	-2476.00	16962.76
Cultivated land with other crops (hectares)	24.03	30.72	0.00	195.40
Pigs	7.82	9.90	0.00	81.80
Total land (hectares)*	91.38	77.99	11.20	427.00
Capital and labour index	148.91	22.21	100.00	193.67

* Total land is the total of land cultivated with winter crops, spring barley, rape and pea

Figure 1: AVERAGE LAND SHARES, UNDEFLATED GROSS MARGINS AND CAPITAL AND LABOUR PRICE INDEX OVER TIME

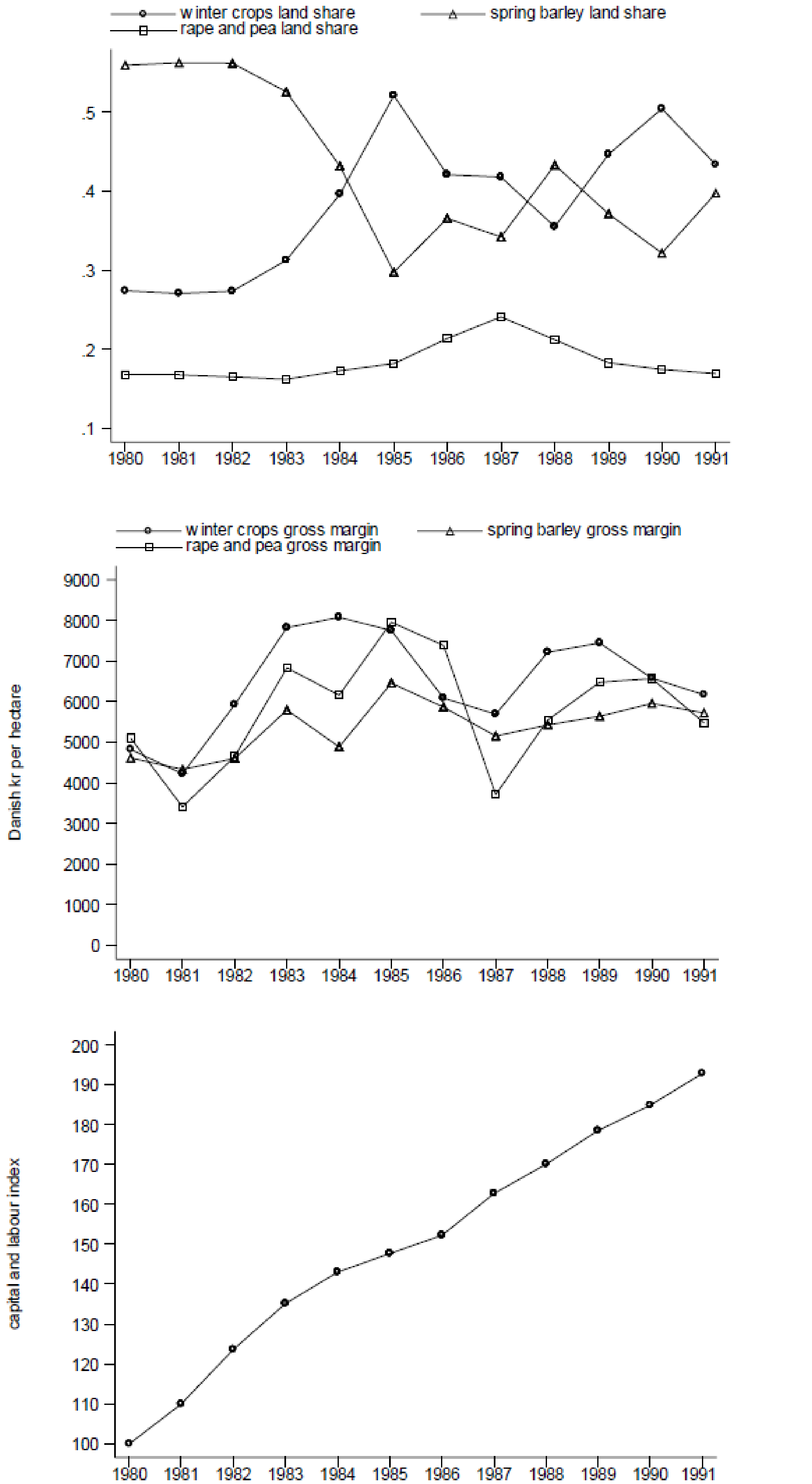


Table 2. Parameter Estimates Dynamic Model

	Unrestricted model		Common Factor Model[1]	Combined Model[1]
Winter Crops Equation:	One step	Two step	One step	One step
Relative winter crop gross margin	1.8 E-5** (8.7 E-6)	1.7 E-5*** (6.3 E-6)	1.7 E-5** (8.6 E-6)	1.7 E-5** (8.4 E-5)
Relative winter crop gross margin (lagged)	6.9 E-5*** (8.7 E-6)	7.1 E-5*** (2.8 E-6)	6.6 E-5*** (7.9 E-6)[2]	6.9 E-5*** (7.4 E-6)[2]
Relative rape & pea gross margin	-1.2 E-5 (8.8 E-6)	-1.5 E-5*** (2.6 E-6)	-4.7 E-6 (4.4 E-6)	-9.3 E-6** (4.4 E-6)
Relative rape & pea gross margin (lagged)	1.8 E-5** (8.7 E-6)	1.7 E-5*** (2.2 E-6)	2.2 E-5*** (7.8 E-6)	1.9 E-5*** (6.5 E-6)
Cultivated land with other crops	3.9 E-3*** (1.0 E-3)	3.9 E-3*** (1.8 E-3)	4.0 E-3*** (1.0 E-3)	4.0 E-3*** (1.0 E-3)
Cultivated land with other crops (lagged)	-1.8 E-4 (1.2 E-3)	-3.7 E-4 (2.7 E-4)	-2.9 E-3 (1.2 E-3)	-2.9 E-4 (1.2 E-3)
Pigs	-6.2 E-4 (2.3 E-3)	-1.2 E-3* (6.7 E-4)	-2.9 E-3 (2.3 E-3)	-3.9 E-4 (2.2 E-3)
Pigs (lagged)	7.4 E-3*** (2.4 E-3)	8.0 E-3*** (7.6 E-4)	7.2 E-3*** (2.4 E-3)	6.9 E-3*** (2.4 E-3)
Total land	-2.3 E-4 (2.7 E-4)	-1.8 E-4*** (5.9 E-5)	-2.2 E-4 (2.7 E-3)	-2.0 E-4 (2.7 E-4)
Lagged winter crop land share	5.3 E-1*** (5.5 E-2)	5.3 E-1*** (1.5 E-2)	5.1 E-1*** (5.4 E-2)	5.2 E-1*** (5.4 E-2)
Rape and Pea Equation				
Relative winter crop gross margin	-1.5 E-6 (4.2 E-6)	-1.3 E-6 (1.4 E-6)	-1.5 E-6 (1.6 E-6)	7.1 E-7 (5.4 E-7)
Relative winter crop gross margin (lagged)	-6.9 E-6 (5.6 E-6)	-7.4 E-6*** (1.6 E-6)	-5.9 E-6 (5.1 E-6)	3.0 E-6* (1.6 E-6)
Relative rape & pea gross margin	-3.0 E-6 (5.5 E-6)	-1.9 E-6 (1.4 E-6)	-5.3 E-6 (4.8 E-6)	-1.1 E-5*** (3.7 E-6)
Relative rape & pea gross margin (lagged)	2.6 E-5*** (4.8 E-6)	2.4 E-5*** (1.2 E-6)	2.5 E-5*** (4.5 E-6)[2]	2.3 E-5*** (4.2 E-6)[2]
Cultivated land with other crops	-4.3 E-4 (6.6 E-4)	-5.1 E-4*** (1.4 E-4)	-4.4 E-4 (6.4 E-4)	-5.2 E-4 (6.4 E-4)
Cultivated land with other crops (lagged)	-5.3 E-4 (6.4 E-4)	-3.0 E-4* (1.8 E-4)	-5.6 E-4 (6.3 E-4)	-4.4 E-4 (6.3 E-4)
Pigs	3.2 E-4 (1.0 E-3)	3.1 E-4 (2.8 E-4)	2.4 E-5 (9.8 E-4)	-9.8 E-5 (9.8 E-4)
Pigs (lagged)	-9.3 E-5 (1.3 E-3)	-2.8 E-4 (3.1 E-4)	7.9 E-5 (1.3 E-3)	2.1 E-5 (1.3 E-3)
Total land	4.8 E-4*** (1.4 E-4)	4.3 E-4*** (3.2 E-5)	4.9 E-4*** (1.4 E-4)	4.3 E-4*** (1.3 E-4)
Lagged rape & pea land share	8.1 E-1*** (7.3 E-2)	8.4 E-1*** (1.6 E-2)	8.2 E-1*** (7.3 E-2)	8.2 E-1*** (7.3 E-2)[2]
Sarg		188 (178) p=0.29		
M2	1.4 p=0.16	1.4 p=0.15		
$Min\ \chi^2$			0.9 (2) p=0.62	4.2 (3) p=0.34

[1] Minimum Chi Square Estimates. [2] Asymptotic standard error derived using the delta method.

* indicates that the parameter is significant at a 10% level. ** indicates that the parameter is significant at a 5% level.

*** indicates that the parameter is significant at a 1% level.

Table 3. Elasticities Dynamic/Static Model

	Dynamic Model			Static Model		
	Winter Crops	Rape and Pea	Spring Barley	Winter Crops	Rape and Pea	Spring Barley
	Mean Gross Margin					
Short Run						
Winter	1.020*** (0.122)	0.065 (0.146)	-0.885*** (0.124)	0.964*** (0.196)	0.359* (0.203)	-1.108*** (0.210)
crops	*0.964*** (0.118)*	*0.181** (0.082)*	*-0.946*** (0.111)*	*0.855** (0.170)*	*0.209* (0.115)*	*-0.883*** (0.153)*
	0.998* (0.118)**	**0.101** (0.046)**	**-0.901*** (0.101)**	**0.962*** (0.177)**	**0.039 (0.034)**	**-0.815*** (0.153)**
Rape	-0.204 (0.166)	0.498*** (0.157)	-0.288** (0.130)	0.038 (0.191)	0.435** (0.197)	-0.427** (0.177)
and pea	*-0.180 (0.158)*	*0.425*** (0.141)*	*-0.241** (0.115)*	*-0.128 (0.157)*	*0.387** (0.198)*	*-0.248* (0.133)*
	0.089* (0.045)	**0.248** (0.104)**	**-0.298*** (0.110)**	**0.090 (0.077)**	**0.075 (0.064)**	**-0.141 (0.120)**
Spring	-0.858*** (0.146)	-0.284* (0.146)	0.954*** (0.128)	-0.915*** (0.240)	-0.530** (0.249)	1.223*** (0.256)
barley	*-0.817*** (0.132)*	*-0.359*** (0.126)*	*0.989*** (0.121)*	*-0.739*** (0.173)*	*-0.369* (0.200)*	*0.934*** (0.188)*
	-0.970* (0.113)**	**-0.205*** (0.079)**	**0.972*** (0.117)**	**-0.936*** (0.169)**	**-0.070 (0.060)**	**0.822*** (0.169)**
Long Run	2.136*** (0.386)	0.137 (0.302)	-1.855*** (0.309)			
Winter	*1.980*** (0.341)*	*0.371** (0.163)*	*-1.942*** (0.297)*			
crops	**2.084*** (0.346)**	**0.210** (0.093)**	**-1.880*** (0.290)**			
Rape	-1.079 (1.023)	2.637** (1.350)	-1.523* (0.866)			
and pea	*-0.988 (1.009)*	*2.330* (1.272)*	*-1.318* (0.793)*			
	0.489 (0.228)**	**1.367 (0.922)**	**-1.640 (1.326)**			
Spring	-1.505** (0.622)	-1.311* (0.694)	2.411*** (0.513)			
barley	*-1.400** (0.587)*	*-1.392* (0.668)*	*2.400*** (0.494)*			
	-2.161* (0.375)**	**-0.810 (0.627)**	**2.487*** (0.493)**			
Adjustment						
proportion[1]	**0.479**	**0.182**	**0.391**			

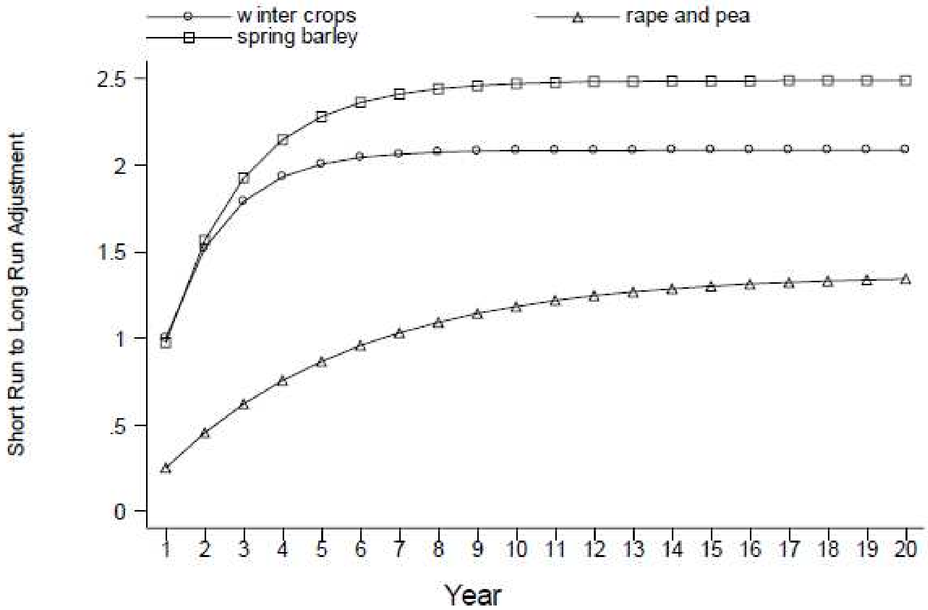
Note: Asymptotic standard errors in brackets are derived using the delta method. In plain, unrestricted estimates. Common factor restricted estimates in italics. In bold, restricted estimates derived from the common factor and the combined,

$D = I - \overline{D}$ and symmetry restriction. [1] Model with all restrictions imposed

* indicates that the parameter is significant at a 10% level. ** indicates that the parameter is significant at a 5% level.

*** indicates that the parameter is significant at a 1% level.

Figure 2: ADJUSTMENT OF LAND SHARES TO CHANGES IN OWN GROSS MARGINS OVER TIME



Note: Each graph shows the adjustment of a land share to a change in its own gross margin over time. For example, the spring barley graph shows the percentage change in the spring barley land share induced by a one percent change in the spring barley gross margin.