2010

RSMG Working Paper Series

Risk and Uncertainty Program

TITLE: Uncertainty and Technical Efficiency in Finnish Agriculture: A State-contingent Approach

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Working Paper: R10_2

Uncertainty and technical efficiency in Finnish agriculture: a state-contingent approach

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Abstract: In this article, we present one of the first real-world empirical applications of state-contingent production theory. Our state-contingent behavioral model allows us to analyze production under both inefficiency and uncertainty without regard to the nature of producer risk preferences. Using farm data for Finland, we estimate a flexible production model that permits substitutability between state-contingent outputs. We test empirically, and reject, an assumption that has been implicit in almost all efficiency studies conducted in the last three decades, namely that the production technology is output-cubical, i.e., that outputs are not substitutable between states of nature.

Uncertainty and technical efficiency in Finnish agriculture: a state-contingent approach

1 Introduction

There is a large literature on comparisons of productive efficiency, beginning with the work of Farrell (1957). Assessments of the relative efficiency of agricultural producers have been of particular interest for a number of reasons. First, because agricultural producers typically own land and live on their farms, the standard assumption that market competition will ensure that only efficient producers remain in a given industry is unlikely to be applicable, and the process of adjustment is likely to cause social problems. Second, there exist a wide range of policy interventions, such as education, training and extension programs, which may be interpreted as attempts to increase the efficiency of agricultural production. Third, policy questions relating to the existence and estimation of an optimal size, or minimum efficient size, for farms have been debated in many countries.

All production is subject to uncertainty, but the risks associated with agricultural production are particularly salient. Crop yields may be affected by the amount and timing of rainfall, temperatures during the growing season, pests, diseases, hailstorms and fire among many other factors. Hence, observed differences in outputs and inputs may reflect differences in efficiency, differences in the outcomes of risky decisions, or both.

One common method for dealing with production uncertainty in efficiency comparisons has been the estimation of stochastic frontier models (see among others, Battese, Rambaldi and Wan, 1997; Kumbhakar 2002; Karagiannis, Tzouvelekas and Xepapadeas, 2003; Morrison Paul and Nehring, 2005). In the standard stochastic frontier model, maximum likelihood estimation is used to partition deviations from an estimated production frontier into two components: a one-sided stochastic term representing technical efficiency and a two-sided term representing exogenous stochastic shocks. Implicitly, the production technology being modelled is stochastic.

In general equilibrium theory and finance theory, among other fields, it is more common to model uncertainty in terms of a state-contingent technology. The origins of state-contingent production theory, which considers that outputs are conditional on the states of nature (each state representing a particular uncertain event) can be traced back to Arrow and Debreu (1954). More recently, Chambers and Quiggin (2000) have shown that all the tools of modern production theory, including cost and distance functions, may be applied to state-contingent production technologies.

Chambers and Quiggin (2000) describe several different types of state-contingent production technologies, including technologies they refer to as *state-allocable*. A feature of state-allocable technologies is that producers can manage uncertainty through the allocation of productive inputs to different states of nature. This concept is best illustrated by a simplified example (Chambers and Quiggin, 2000, pp. 36–39). Consider a producer who makes a pre-season allocation of a fixed amount of effort to construction of irrigation infrastructure and/or flood-control facilities. If the producer allocates his pre-season effort to the development of irrigation facilities instead of flood control, output will be relatively high if there happens to be a drought (state 1) and low in the event of a flood (state 2). Conversely, if pre-season effort is allocated mainly to flood control, output will be relatively high in state 2 and low in state 1. In this simple example, different pre-season allocations of the input imply a trade-off between output realized in state 1 and output realized in state 2. That is, the producer allocates the input to different states of nature in order to effect a substitution between state-contingent outputs.

The state-contingent approach, by permitting the allocation of productive inputs to different states of nature, recognizes that actions (input choices) can have different consequences in different states of nature. This is not a property of conventional stochastic production theory, in which the role that inputs play remains the same regardless of which state occurs, and which does not permit substitutability between state-contingent outputs. The different types of state-contingent technology described by Chambers and Quiggin allow for more or less substitutability between state-contingent outputs. A technology that does not permit any substitutability between state-contingent outputs is referred to as *output-cubical* (such a technology is Leontief in state-contingent outputs).

Whereas, on the one hand, the theory of state-contingent production is now well established, on the other hand, empirical implementation of the state-contingent approach is still in its infancy. The most notable applications to efficiency analysis are O'Donnell and Griffiths (2006), O'Donnell, Chambers and Quiggin (2010), Chavas (2008), and more recently Serra et al. (2010). O'Donnell and Griffiths (2006) have used a Bayesian approach to estimate an output-cubical state-contingent production frontier for rice farmers from the Philippines. They show that, where state-contingent uncertainty plays a major role, the stochastic frontier approach may lead to significant overestimation of the inefficiency of some producers. Indeed, the part of the deviation from the frontier that was due to risk was misinterpreted as inefficiency in the conventional stochastic frontier model. Chavas (2008) and Serra et al. (2010) estimate a state-contingent cost function using aggregated data from the United States (1949–1999 annual series). The results generated using this data provide empirical support for an output-cubical technology.

O'Donnell, Chambers and Quiggin (hereafter OCQ) have used simulated data to estimate a stochastic frontier which allows for state-allocable inputs. They show that, where technically efficient producers make state-contingent production plans under conditions of uncertainty, standard techniques of efficiency analysis such as Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) may produce spurious findings of inefficiency. Indeed, in a state-contingent framework, such producers are judged to have merely encountered a state of nature that is unfavourable, given their state-contingent production plan, and need not necessarily be inefficient. For example, a producer may choose to use a low level of pesticides because the expected return is negative. In states of nature leading to a severe pest infestation, output will be low.[1]

Overall, this small set of empirical studies indicates that, in uncertain decision environments, conventional stochastic production frontier models can provide a restrictive and unrealistic representation of the production process, and can lead to significantly biased estimates of measures of technical efficiency. In this article, we propose an empirical methodology to

[1] Kumbhakar (2002) shows the importance of controlling for both risk and inefficiency in an expected utility framework.

test whether the underlying production technology is output-cubical on real data. We specify a CES-type production technology that encompasses well-known functional forms including the Leontief and the Cobb-Douglas production functions. Our model is also a generalization of the state-allocable model of OCQ in the sense that output in a particular state of nature can still be non-zero even when none of the input has been allocated to that state (such an input is said to be *state-general*).[2] We show how this multiple-input state-allocable model can be estimated within a frontier framework, which allows us to estimate levels of input-allocability and technical efficiency using farm data from Finland.

The paper is organized as follows. The theoretical model, which is an extension of OCQ (2010), is described in Section 2. In Section 3, we present the empirical application, including a discussion of model specification, description of data, and discussion of estimation results. Section 4 concludes.

2 Description of the technology

In OCQ (2010), the technology of production is modeled as follows:

$$\ln q_s = b^{-1}(\ln x_s - \ln a_s) \tag{1}$$

where q_s denotes output realized in state $s \in \Omega = (1, 2, \ldots, S)$ and x_s is the amount of input x allocated to state s. OCQ assume that the producer chooses x_s for all values of s before the uncertainty is resolved (that is, before s is known). The unknowns satisfy $b \geq 1$ and $a_s \geq 0$ for all s. The input is state-specific in the sense that output in state s is zero if no input has been allocated to that state.

The parameters a_s can be thought of as technical parameters that are specific to the production of output in state s. The parameter b is interpretable as the cost flexibility associated with production in state s and, as will be explained below, will thus indicate the extent to which the state-contingent outputs are substitutable. For fixed x, the marginal rate of transformation (MRT) between ex post outputs in states s and s' is given by:

[2] An overly restrictive feature of the single-input model of OCQ is that the (single) input is *state-specific* in the sense that output realized in a particular state of nature will be zero if none of the input has been allocated to that state.

$$MRT = -\left(\frac{a_s}{a_{s'}}\right)\left(\frac{z_s}{z_{s'}}\right)^{b-1}$$

and hence the elasticity of transformation between any pair of ex-post outputs is a constant:

$$\sigma = \left|\frac{d\ln(z_s/z_{s'})}{d\ln|MRT|}\right| = \frac{1}{1-b}.$$

As $b \to 1$, the elasticity of transformation tends to infinity and the state-contingent production transformation curve tends to a linear function which corresponds to perfect substitutability between state-contingent outputs. As $b \to \infty$, the elasticity of transformation converges to zero, no substitution between state-contingent outputs is possible (the state-contingent transformation curve is Leontief in outputs) and the production technology is output-cubical (OCQ, 2010).

This model proved useful with simulated data but it has some unrealistic properties that limit its usefulness when analysing real data. First, the restriction $b \geq 1$ implies the technology exhibits non-increasing returns to scale. Second, the input is state-specific in the sense that output in state s is zero if there is no input allocated to that state. Third, there is only one input into the production process, this input being state-allocable. In this article, we propose the following more flexible CES-type model:

$$q_s = A_s\left[\theta^b x^b + \delta_s^b x_s^b + \sum_{k=1}^{K} \gamma^b z_k^b\right]^{\phi/b} \tag{2}$$

where $b \neq 0$; $\phi > 0$; $A_s \equiv a_s^{-1/b} \geq 0$ and z_k $(k = 1, \ldots, K)$ is a non-state-allocable input. This functional form is more flexible in the sense that the technology can exhibit increasing, constant or decreasing returns to scale (RTS) as ϕ is less than, equal to, or greater than one. We consider one state-allocable input x_s but we allow for output in state s to be non-zero even if $x_s = 0$ by incorporating in the production function the total input use $x = \sum_{s=1}^{S} x_s$. The parameter δ is a measure of how output in state s responds to an input allocation to that particular state.[3] Our model also contains some non-allocable inputs z_k. Model (2) can

[3] In the empirical application, we will also test if output in state s responds to input allocations to states other than s.

also be equivalently written in the form:

$$\ln q_s = \ln A_s + \phi b^{-1} \ln \left[\theta^b x^b + \delta_s^b x_s^b + \sum_{k=1}^{K} \gamma^b z_k^b \right] \tag{3}$$

Some special cases are of interest:

- (Leontief) $\phi = 1, b \to -\infty \Rightarrow q_s \to A_s \times \min(\alpha x, \beta_s x_s, \zeta_1 z_1, \ldots, \zeta_K z_K)$

- (Cobb-Douglas) $\phi = 1, b \to 0 \Rightarrow q_s \to A_s x^\theta x_s^{\delta_s} \prod_{k=1}^{K} z_k^{\gamma_k}$

- (Conventional Frontier) $\phi = 1, A_s = A \forall s; \delta_s = 0; b \to 0 \Rightarrow q_s \to A x^\theta \prod_{k=1}^{K} z_k^{\gamma_k}$

- (OCQ) $\theta = 0; \phi = b^{-1}; \delta_s = 1; \gamma_k = 0 \forall k \Rightarrow q_s = A_s x_s^{1/b}$

- (linear) $\phi = b = 1 \Rightarrow q_s = A_s \left[\theta x + \delta_s x_s + \sum_{k=1}^{K} \gamma_k z_k \right]$

- (output-cubical) $\delta_s = 0 \Rightarrow q_s = A_s \left[\theta^b x^b + \sum_{k=1}^{K} \gamma_k^b z_k^b \right]^{\phi/b}$.

If the parameter $b \to -\infty$, there is no substitution possibility between the state-contingent outputs, and the state-contingent production transformation curve tends to a function which is Leontief in outputs. If $b \to 0$, the production function collapses to a Cobb-Douglas. In these two cases, the state-specific state-allocable input (x_s) enters into the production function. If $b \to 0$ and allocation of inputs x between states is not taken into account (i.e., $\delta_s = 0$), then the model collapses to a conventional frontier. The OCQ model as described in (1) is obtained under the following restrictions: $\theta = 0; \phi = b^{-1}; \delta_s = 1; \gamma_k = 0 \forall k$. If $\phi = b = 1$, the technology is linear and exhibits constant RTS. Finally, if the allocation of the input x across states is not taken into account (i.e., $\delta_s = 0$), the model collapses to a pure output-cubical production function.

If $b \neq 0$, then the elasticities that measure output responses to increases in inputs as obtained from the general CES-type model (3) are:

$$\eta_s \equiv \frac{\partial \ln q_s}{\partial \ln x_s} = \frac{\partial \ln q_s}{\partial x_s} \times x_s = \frac{\phi\left(\theta^b x^{b-1} x_s + \delta_s^b x_s^b\right)}{\theta^b x^b + \delta_s^b x_s^b + \sum_{k=1}^{K} \gamma^b z_k^b} \tag{4}$$

$$\xi_{sj} \equiv \frac{\partial \ln q_s}{\partial \ln z_j} = \frac{\partial \ln q_s}{\partial z_j} \times z_j = \frac{\phi \gamma_j^b z_j^b}{\theta^b x^b + \delta_s^b x_s^b + \sum_{k=1}^{K} \gamma^b z_k^b} \tag{5}$$

3 Empirical illustration

3.1 Specification of the model

Embedding model (3) in a stochastic framework yields:

$$\ln q = \sum_{s=1}^{S} e_s \ln A_s + \phi b^{-1} \ln \left[\theta^b x^b + \sum_{s=1}^{S} e_s \delta_s x_s^b + \sum_{k=1}^{K} \gamma^b z_k^b\right] + v - u \tag{6}$$

where e_s is a dummy variable that takes the value 1 when nature chooses state s (and 0 otherwise); the v's are independently and identically distributed normal random variables with zero means and variance σ_v^2 representing statistical noise; and the u's are independently and identically distributed half-normal random variables with scale parameter σ_u^2 representing technical inefficiency. In our empirical work we parameterise the likelihood function in terms of $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$. We estimate a conventional frontier model (CF), the OCQ frontier model, and two special cases of our flexible frontier model corresponding to the following values of the parameter b: 0 and 1, respectively called FLEX0 and FLEX1.[4] These four models, which are specified such that they accommodate zero inputs, are written as follows:

$$\text{CF:} \qquad \ln q = \ln A + \theta \ln x + \sum_{k=1}^{K} \gamma_k h_k \ln z_k + v - u$$

$$\text{OCQ:} \qquad \ln q = \sum_{s=1}^{S} e_s \ln A_s + \frac{1}{b} d_s \ln x_s + v - u$$

[4] The estimation of the parameter b is left for future research.

$$\text{FLEX0}: \quad \ln q = \sum_{s=1}^{S} e_s \ln A_s + \theta \ln x + \sum_{s=1}^{S} \delta_s e_s d_s \ln x_s + \sum_{k=1}^{K} \gamma_k h_k \ln z_k + v - u$$

$$\text{FLEX1}: \quad \ln q = \sum_{s=1}^{S} e_s \ln A_s + \phi \ln \left[\theta x + \sum_{s=1}^{S} \delta_s e_s d_s x_s + \sum_{k=1}^{K} \gamma_k h_k z_k \right] + v - u,$$

where $d_s = I(x_s > 0)$, $h_k = I(z_k > 0)$ and $I(.)$ is an indicator function that takes the value 1 if the argument is true and 0 otherwise.[5] The error term in model FLEX0 subsumes any errors associated with the fact that this Cobb-Douglas model is only the limiting model as $b \to 0$ (i.e., is not exact). In every case there is interest in whether firms are fully technically efficient (i.e., $H_0 : \lambda = 0$). In the FLEX models, interest also centres on whether the technology is output-cubical (i.e., $H_0 : \delta_s = 0 \forall s$).

3.2 Data

The data have been taken from the Finnish profitability bookkeeping records (which serve as a basis for the European Commission's Farm Accountancy Data Network survey) and cover the 1998–2003 period. The data comprise annual farm-level observations on acreage allocated to each crop, crop output, and expenditures on labour, pesticides and fertilizers.[6] The sample used in our analysis considers specialized grain farmers from southern regions in Finland, the main grain production area in the country. These data were complemented by weather data (rainfall, temperature, and the starting date of the growing season) for each province produced by the Finnish Meteorological Institute. Data on input and output prices have been collected from Finnish Agriculture and Rural Industries, an annual report of Finnish agriculture. Our sample is an unbalanced panel of 274 farmers from 17 provinces over the 1998–2003 period, making a total of 1,020 observations. For greater details on the data, see Koundouri et al. (2009).

Finnish farmers face different types of risk but production risk due to unstable weather conditions (frost may occur in the middle of the summer) is recognized as the main source

[5] Thus, we replace logarithms of variables with zero whenever the variables take the value zero.

[6] As is often the case with agricultural data sets, expenditures on labour, pesticides and fertilizers are not disaggregated by crop.

of risk for cereal producers in Finland.[7] Cereal producers have been found to be risk-averse before Finland's European Union (EU) accession in 1995 and risk-lovers after, due to the increase in the non-random part of farm income generated by the policy change after application of the Common Agricultural Policy (Koundouri et al., 2009).[8] For the period under consideration in this article (1998–2003), the risk premium has been estimated between -1 and -2 percent of farmer's profit (see Koundouri et al., Table 2). In this context, Finnish farmers can be considered risk-neutral over the 1998-2003 period.

Because of the primary role of production risk, we define (based on our discussions with Finnish grain specialists) the states of nature in terms of two meteorological variables: the starting date of the growing season and the sum of rainfall in June. The starting date of the growing season (measured as a number of days from January 1st) is defined as the period of each year with daily mean temperatures above +5 Celsius degrees, which is the temperature at which soil is sufficiently thawed for root activity to begin. The starting date of the growing season is a relevant variable to be used in the definition of the states of nature because the decision of which crop to grow is made in general one to two months before sowing for the main reason that seeds have to be bought in advance. The comparison of average crop yields under different conditions (early, average, and late start of the growing season, and low, average and high sum of rainfall) permits identification of three states: a state of nature that is most favourable to the growing of wheat ($s = 1$), a state of nature that is most favourable to the growing of barley ($s = 2$), and a state of nature that is most favourable to the growing of oats ($s = 3$), see Table 1.[9]

[Table 1 around here]

Table 1 reads as follows: an early start of the growing season combined with a low [respectively average, and high] rainfall in June is most favourable to barley [resp. oats, and

[7] Liu and Pietola (2005) showed that yield volatility is large and dominates price volatility in the hedging decisions of Finnish wheat producers.

[8] After entering the EU, target prices were replaced by substantially lower intervention prices while direct area payments became the corner stone of agricultural support.

[9] The comparison of crop yields has been made on a sub-sample of observations since information on yields is missing for some farmers.

barley]. That is, the highest average yields are observed on average for barley [respectively oats, and barley]. An average starting date of the growing season is always favourable to wheat production. A late start of the growing season combined with a low [respectively average, and high] rainfall is most favourable to barley [respectively wheat, and wheat]. Hence, for each observation (a farmer in a specific year), based on the observation of the starting date of the growing season and the sum of rainfall in June in the province (we have 17 such provinces), we know whether the realized state of nature was wheat-favourable, barley-favourable or oats-favourable. In Table 2, we report the number of farmers experiencing each of the three states, for each year covered by our sample.

[Table 2 around here]

In our model, and due to data availability, only land (x) is regarded as state-allocable. Land qualifies as a suitable state-allocable input because land allocation is a decision taken at the beginning of the growing season, before the farmer knows which state of nature will be realized. Also, it relies on the reasonable assumption that farmers allocate the land input to the production of wheat, barley and/or oats, in line with subjective risk-neutral probabilities attached to states of nature that are considered favourable to the production of each of those crops. Land allocated to wheat, barley and oats is denoted x_1, x_2, and x_3, respectively. For each farmer and each year, we have $x = x_1 + x_2 + x_3$, with $x_k \geq 0$ for $k = 1, 2, 3$. Basic statistics of the main variables of interest are shown in Table 3.

[Table 3 around here]

In our model, the output variable is an implicit quantity index obtained by dividing the total value of production of wheat, barley and oats by an output price index.[10] The use of a single output instead of a multi-output technology (in which barley, wheat, and oats outputs would be considered separately) is a limitation of our analysis. This choice is explained by

[10] The use of a single output index (instead of a multi-output vector) is rather common. For example, statistical agencies such as the USDA routinely aggregate many different crop outputs into a single crop output index. Also Chavas (2008) and more recently Serra et al. (2010) have developed applications of the state-contingent theory using annual data on US agriculture by considering one aggregate output.

the lack of appropriate instruments that would be necessary to overcome the endogeneity problem inherent to multi-output functional forms.

We consider four inputs: land (x), labour (which corresponds to total working hours in crop production, including both hired labour and family labour) (z_1), capital (defined as the total value of fixed assets on the farm) (z_2), fertilizers (z_3) and plant protection (z_4).[11]

3.3 Estimation results

The estimation of the four models is made using Maximum-Likelihood, without taking into account the panel form of the data.[12]

[Table 4 around here]

We report estimated coefficients and corresponding t-ratios for the four models: Conventional Frontier (CF), OCQ, FLEX0, and FLEX1. The Akaike's information criterion (AIC), computed as $2 \times k - 2 \times \log\mathrm{L}$ (where k is the number of parameters and log-L is the value of the log-likelihood function), indicates that the FLEX1 model is preferred. The null assumption that the underlying technology is output-cubical (or equivalently that outputs are not substitutable between states) corresponds to a test of $\delta_s = 0 \forall s$ in both the FLEX0 and FLEX1 models. This assumption is rejected at usual levels of significance for the two models. Based on these results, the FLEX1 model is considered the best fit to our data, followed by the FLEX0 model, the CF, and the OCQ model.[13] Our result that the underlying technology is not output-cubical contrasts with Chavas (2008) and more recently Serra et al. (2010). However, the setting in these two papers differed from ours: they estimated

[11] Seed is potentially another important input. Unfortunately, our data do not contain expenditure on seed as a separate item. Note however that, if sowing rates (i.e., kilograms of seed per hectare) for each crop are constant across observations then seed does not need to be included as a separate input (because, in this case, it would be proportional to the land input).

[12] We faced convergence problems when considering farmer-specific unobserved heterogeneity in our model.

[13] In Appendix, we report the estimated coefficients of the model in which land allocated to all three states enter as possible drivers of output in state s. This model, estimated under the assumption that $b = 0$ and $b = 1$, is called respectively FLEX0-EXT and FLEX1-EXT. The AIC criterion indicates that FLEX1-EXT dominates FLEX0-EXT.

cost-minimizing input choices (in a static framework in Chavas, and in a dynamic framework in Serra et al.) with a state-contingent technology using aggregate data (for the US) and allowed for two states of nature only.

The estimated coefficients for the FLEX0 and FLEX1 models are consistent with theoretical expectations, except for the δ coefficient on the oats-favourable state (δ_3). This is negative, implying that an increased allocation of land to oats, at the expense of wheat and barley, will reduce output even in the oats-favourable state. Note however that the negative coefficient on δ_3 does not imply a negative marginal product for land allocated to oats, since the coefficient on total land area x is positive.[14]

One possible explanation for the negative coefficient of the parameter δ_3 is that land allocated to oats production tends to be of relatively low quality. Finland is divided into support regions which were defined when Finland entered into the European Union (EU) in 1995. These support regions were defined based on soil type and climatic conditions since they determine the level of per hectare crop subsidies received by the farmers from the EU. Our sample covers four of these support regions: A, B, C1 and C2. Crop yields are usually higher in region A than in region B, and higher in B than in regions C1 and C2. In terms of crop choice, wheat and barley dominate in region A: 59% of the land is allocated to wheat and 35% is allocated to barley on average (the rest, 6%, is allocated to oats). In region B and in region C1, 40% of the land is allocated to oats on average (and only 12% to wheat); in region C2 (i.e. the region with the least favourable conditions for crop growing), 54% of the land is allocated to oats. This problem might be addressed by making a quality adjustment for land area. Unfortunately our data set does not provide sufficient information for this purpose.

The coefficients (γ_1, γ_2, γ_3, and γ_4) of the non-allocable inputs (labour, capital, fertilizers and plant protection) are all found to be positive and significant at usual levels in most cases, but vary across specifications. The parameter θ is found to be different from 0 in all models, which indicates that land in our model is state-general, in the sense that output in

[14]In fact, the marginal effect of land allocated to oats (x_3) on output has the same sign as the output elasticity and our estimates of all the output elasticities have indeed the expected positive sign (see Table 5).

state s is non-zero even if none of the land has been allocated to that state. For example, output will be strictly positive even for a farmer who planted only wheat and barley in an oats-favourable state.

The null assumption that $\lambda = 0$ is rejected at usual levels of significance for every model, showing evidence of technical inefficiency. The average technical inefficiency score is 0.63 in FLEX1 model, close to what is obtained using the FLEX0 model and the CF. On these data, the average estimated technical inefficiency scores are found to be similar between state-contingent models and more restrictive models (in particular the conventional frontier). This may indicate that output shortfalls due to unfavourable states of nature are small compared to output shortfalls due to technical inefficiency.

A simple comparison of the average technical inefficiency scores across the different models may be misleading, though. We looked more closely at the distribution of technical inefficiency scores across the different models but, in what follows, we focus on the comparison between technical inefficiency scores calculated from the CF model (the "conventional" approach) and those calculated from the FLEX1 model (the preferred model based on Akaike's criterion). We made some mean comparison tests and tests of equality of distributions of technical inefficiency scores between favourable and unfavourable states. For each farmer and each year, we know how much land was allocated to wheat, barley, and oats. We call wheat-producers those farmers who allocated the largest share of their land to wheat. Barley- and oat-producers are similarly defined. We consider that wheat producers in a particular year encountered a favourable state if the realized state of nature was the one most favourable to wheat-growing (same for barley and oats). Because the state-contingent model does take uncertainty into account (and does allow for output substitution between states), we would expect that technical inefficiency scores are about the same whatever the state of nature (favourable or unfavourable). On the contrary, the CF approach does not account for uncertainty and technical inefficiency scores are likely to be improperly calculated (in particular, technical inefficiency scores are likely to differ between favourable and unfavourable states). We test the null hypothesis that the average technical inefficiency score is the same between favourable and unfavourable states of nature, separately for wheat producers, barley producers, and oat producers. The mean comparison test using CF-based technical inefficiency scores always rejects the null that the two means are equal. The mean comparison test using FLEX1-based technical inefficiency scores does not reject the null hypothesis at usual levels of significance.

We then performed a Kolmogorov-Smirnov equality-of-distributions test for wheat and barley producers (we have too few observations on oat producers in a favourable state for the test to be meaningful). The test of equality of distributions confirms that the distribution of CF-based technical inefficiency scores differs between favourable and unfavourable states while the distribution of FLEX1-based technical inefficiency scores is not found to be statistically different between favourable and unfavourable states. So, on our data, the distribution of technical inefficiency scores calculated with the CF model is significantly different between favourable and unfavourable states, while it is not if calculated with the preferred FLEX1 model. These findings confirm that not taking uncertainty into account in the specification of the technology may provide misleading technical inefficiency scores.

Estimated supply response elasticities and returns to scale are shown in Table 5.

[Table 5 around here]

We report (estimated) elasticities of output in the three states with respect to the amount of land allocated to each of those states (η_{sk} for $s, k = 1, 2, 3$) as well as the elasticity of output with respect to the four non-allocable inputs (ε_k for $k = 1$ to 4). The elasticities have been evaluated at the sample means of x, z_1, z_2 , z_3 and z_4 (see Table 3 for mean values). In the FLEX1 model, the state-specific elasticities of output vary between 0.14 and 0.47.[15] In each state ($s = 1, 2, 3$), the elasticity of output with respect to total land is close to 0.9, which makes sense knowing that land is an essential input in crop production. The elasticities of output with respect to capital and variable inputs (labour, fertilizers, and plant protection) may seem low (they vary between 0.03 and 0.21), in particular if compared with output elasticities obtained by Koundouri et al. (2009). However, the sum of all elasticities gives a

[15] We can see that the elasticity of output with respect to land allocated to state 2 is always higher than the elasticity with respect to land allocated to state 1, which in turn is always higher than the elasticity with respect to land allocated to state 3. This is because the elasticities are a function of land shares and the average share allocated to state 2 is higher than the average share allocated to state 1 which is higher than the average share allocated to state 3.

returns to scale elasticity of about 1.2, which seems reasonable, and indicates that farms in our sample are operating in the region of increasing returns to scale. In the near future, we hope to be able to get data on state-contingent allocations of all inputs used in production, which should provide more robust measures of the marginal productivity of variable inputs. Note also that elasticities of output with respect to variable inputs estimated from the CF model are of the same magnitude as the elasticities estimated from the preferred FLEX1 model.

4 Conclusions

In this article, we present one of the first real-world empirical applications of state-contingent production theory. Our state-contingent behavioral model allows us to analyze production under both inefficiency and uncertainty without regard to the nature of producer risk preferences. Using farm data for Finland, we estimate a flexible production model that permits substitutability between state-contingent outputs. Our model extends the theoretical model described in OCQ (2010) by allowing for a state-general input as well as multiple non-allocable inputs. In our application, we treat land as a state-allocable input, and we specify four non-allocable inputs (labour, capital, fertilizers and pesticides). Uncertainty is represented by three states of nature, defined in terms of climatic conditions (rainfall and start of the growing season): a wheat-favourable state, a barley-favourable state, and an oats-favourable state.

We test empirically, and reject, an assumption that has been implicit in almost all efficiency studies conducted in the last three decades, namely that the production technology is output-cubical. Our results indicate that a state-allocable state-contingent production model is preferred to the more restrictive output-cubical state-contingent model, as well as a conventional stochastic frontier.

The existence of a state-allocable production technology has a number of important implications for agricultural production under uncertainty and for policy responses to the problems of agriculture. First, the value of timely information about the state of nature is maximized with a state-allocable technology. By contrast, under an output-cubical model, producers can respond to information by changing the scale of production but not by reallocating inputs towards states of nature that appear more likely in the light of new information (Chambers and Quiggin, 2007).

In policy terms, producers with a state-allocable production technology have a capacity to manage production risk actively, and to integrate technological and financial approaches to risk management (Chambers and Quiggin, 2004). Policies designed to mitigate risk should complement, rather than substitute for the risk management strategies available to farmers.

The estimation of state-contingent technologies is in its infancy, but it has shown that assumptions derived from an output-cubical model must be treated with care. This study has shown, on the one hand, how data on the allocation of a single input (land) can be used to derive insights into the nature of technology, and on the other hand, how much more is needed. With improved data and estimation methods, our understanding of production under uncertainty will be further enhanced.

Our analysis suffers from some caveats. First, the specification of the technology was constrained by the lack of data and by problems to reach convergence when maximizing the likelihood function. A multi-output technology may provide further insights but this requires finding appropriate instruments to deal with the inherent endogeneity problem. Second, land was the only input to be assumed state-allocable while farmers may also allocate labour or plant protection products across states. We expect in the near future to be able to access disaggregated data on input expenditure by crop or farm type of activity. This would allow us to better represent farmers' decisions when facing uncertainty and to calculate more accurate output supply elasticities and technical inefficiency scores. A third caveat of our empirical analysis is that the parameter measuring substitution between state-contingent outputs could not be estimated. Finally, we were not able to control for the panel form of the data by incorporating farmers' unobserved individual effects. Our production technology also did not explicitly account for technical change. These limitations should be addressed in future research.

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Tables

Table 1: Definition of crop-favourable states based on average crop yield (kg/ha)

		Starting date		
	Crop	Early	Average	Late
Low rainfall	Barley	**3,057**	3,184	**3,098**
	Oats	2,872	3,072	2,853
	Wheat	2,985	**3,392**	2,717
Average rainfall	Barley	3,349	3,329	3,381
	Oats	**3,597**	3,294	3,265
	Wheat	3,478	**3,436**	**3,392**
High rainfall	Barley	**3,292**	3,286	2,984
	Oats	3,138	3,288	2,987
	Wheat	2,778	**3,540**	**3,774**

Table 2: Distribution of farmers across states, by year

Year	Wheat-favourable state (s=1)	Barley-favourable state (s=2)	Oats-favourable state (s=3)	Total
1998	123	16	28	167
1999	20	124	13	157
2000	26	33	102	161
2001	170	0	0	170
2002	150	0	20	170
2003	126	48	21	195
Total	615	221	184	1,020

Table 3: Descriptive statistics of the main variables

Variable	Unit	Mean	Std. Dev.	Min	Max
land (x)	*ha*	38.58	30.94	1.61	233.78
land to wheat (x_1)	*ha*	11.53	20.53	0	157.07
land to barley (x_2)	*ha*	18.55	23.27	0	211.76
land to oats (x_3)	*ha*	8.49	10.42	0	89.15
labour (z_1)	*hours/year*	876	789	0	12319
capital (z_2)	*quantity index*	199,219	155,220	4,989	1,022,397
fertilizers (z_3)	*quantity index*	3,968	4185	0	27,837
plant protection (z_4)	*quantity index*	1,837	2,422	0	25,027

Table 4: Estimation results

	CF		OCQ		FLEX0		FLEX1	
	Est.	t-ratio	Est.	t-ratio	Est.	t-ratio	Est.	t-ratio
A	3.372	13.065	-	-	-	-	-	-
$\sqrt{A1}$	-	-	-	-	-	-	0.227	8.550
$\sqrt{A2}$	-	-	-	-	-	-	0.207	8.423
$\sqrt{A3}$	-	-	-	-	-	-	0.249	8.161
$\ln A_1$	-	-	9.716	117.030	3.839	14.377	-2.967	n.a.
$\ln A_2$	-	-	9.185	84.893	3.616	13.322	-3.146	n.a.
$\ln A_3$	-	-	10.138	93.538	4.052	14.487	-2.782	n.a.
θ	0.910	33.305	-	-	0.893	31.841	854.570	19.577
δ_1	-	-	-	-	0.054	4.444	239.320	4.109
δ_2	-	-	-	-	0.054	2.534	219.970	2.395
δ_3	-	-	-	-	-0.068	-2.840	-225.070	-2.760
γ_1	0.089	4.384	-	-	0.089	4.491	1.467	1.608
γ_2	0.208	8.288	-	-	0.170	6.512	0.034	5.503
γ_3	0.009	1.555	-	-	0.008	1.428	0.519	2.093
γ_4	0.025	3.826	-	-	0.023	3.471	1.920	4.145
ϕ	-	-	0.323	15.229	-	-	1.205	59.641
σ	0.723	31.954	1.410	24.784	0.697	32.361	0.703	32.904
λ	3.011	9.697	1.946	7.951	2.927	11.003	3.234	10.195
Log-L	-637.002		-1423.751		-604.519		-592.754	
AIC$^{(a)}$	649.002		1431.751		626.519		622.754	
LR for H_0: OC$^{(b)}$					30.842		26.958	
p-value					0.000		0.000	
TE	0.623		0.461		0.633		0.629	
95% CI low. bound	0.215		0.060		0.228		0.222	
95% CI upp. bound	0.979		0.962		0.980		0.979	

(a) AIC $= 2 \times k - 2 \times$ Log-L where k is the number of parameters.

(b) The H_0 assumption of an output-cubical (OC) model corresponds to: $H_0 : \delta_1 = \delta_2 = \delta_3 = 0$.

Table 5: Supply response elasticities and returns to scale (RTS)

	CF	OCQ	FLEX0	FLEX1
Elasticities with respect to x_1, x_2 and x_3				
η_1	0.272	-	-	-
η_2	0.438	-	-	-
η_3	0.200	-	-	-
η_{11}	-	0.323	0.321	0.308
η_{12}	-	0.000	0.429	0.387
η_{13}	-	0.000	0.197	0.177
η_{21}	-	0.000	0.267	0.234
η_{22}	-	0.323	0.484	0.474
η_{23}	-	0.000	0.197	0.172
η_{31}	-	0.000	0.267	0.266
η_{32}	-	0.000	0.429	0.427
η_{33}	-	0.323	0.129	0.144
Elasticities with respect to z_1, z_2, z_3 and z_4				
ξ_1	0.089	0.000	0.089	-
ξ_2	0.208	0.000	0.170	-
ξ_3	0.009	0.000	0.008	-
ξ_4	0.025	0.000	0.023	-
ξ_{11}	-	-	-	0.031
ξ_{12}	-	-	-	0.166
ξ_{13}	-	-	-	0.050
ξ_{14}	-	-	-	0.086
ξ_{21}	-	-	-	0.031
ξ_{22}	-	-	-	0.161
ξ_{23}	-	-	-	0.049
ξ_{24}	-	-	-	0.084
ξ_{31}	-	-	-	0.035
ξ_{32}	-	-	-	0.183
ξ_{33}	-	-	-	0.055
ξ_{34}	-	-	-	0.095
Returns to scale (RTS)				
RTS	1.241	0.323	-	1.205
RTS1	-	-	1.236	-
RTS2	-	-	1.237	-
RTS3	-	-	1.115	-

Appendix

Table A1: Estimation results

	FLEX0-EXT		FLEX1-EXT	
	Est.	t-ratio	Est.	t-ratio
$\sqrt{A1}$	-	-	0.080	1.853
$\sqrt{A2}$	-	-	0.066	1.892
$\sqrt{A3}$	-	-	0.082	1.745
$\ln A_1$	3.977	13.799	-5.046	n.a.
$\ln A_2$	3.648	12.519	-5.432	n.a.
$\ln A_3$	4.004	13.516	-4.999	n.a.
θ	0.880	23.311	11452.000	0.925
δ_{11}	0.055	3.312	-2604.600	-0.688
δ_{12}	0.010	0.601	-4240.600	-0.780
δ_{13}	-0.013	-0.755	-4969.500	-0.827
δ_{21}	-0.024	-1.040	-4763.600	-0.761
δ_{22}	0.075	2.857	-600.660	-0.216
δ_{23}	0.045	1.758	-2033.800	-0.532
δ_{31}	0.056	2.087	-2653.700	-0.795
δ_{32}	0.018	0.667	-4244.800	-0.876
δ_{33}	-0.028	-0.911	-5343.900	-0.897
γ_1	0.085	4.253	15.040	1.011
γ_2	0.165	6.268	0.316	0.963
γ_3	0.008	1.350	4.082	0.965
γ_4	0.021	3.313	16.796	0.965
ϕ	-	-	1.169	47.438
σ	0.694	34.919	0.696	32.862
λ	2.965	11.766	3.168	9.969
Log-L	-597.494		-585.837	
AIC$^{(a)}$	631.494		627.837	
LR for H_0: OC$^{(b)}$	44.892		40.792	
p-value	0.000		0.000	
TE	0.634		0.632	
95% CI lower bound	0.229		0.226	
95% CI upper bound	0.980		0.980	

(a) AIC $= 2 \times k - 2 \times$ Log-L.

(b) $H_0 : \delta_1 = \delta_2 = \delta_3 = 0$.