



Original Articles

An indicator for nature-state detection in the state-contingent framework and the case of grain production in Saxony-Anhalt, Germany



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ARTICLE INFO

Keywords:

Agricultural production analysis under uncertainty
State-contingent production
Detection of the states of nature
Indicator development

ABSTRACT

Sound policy needs tools for production analysis under uncertainty such as the state-contingent approach. Apart from demonstrating the potential applicability of the approach for the grain producing sector in Saxony-Anhalt, Germany, this contribution addresses one of the key challenges to its empirical applications in the context of agricultural production analysis under uncertainty, namely the definition of the states of nature and the construction of environmental indicators to detect the occurrence of the so-defined states. This study proposes such an environmental indicator based on biophysical crop yields and suggests two methods for statistical data clustering to evaluate its values. To the extent to which simulated data reflect key characteristics of the real data this contribution presents estimates for the state-contingent production technology. The hypothesis of an output-cubical technology is rejected in contradiction to assumptions implicit to conventional production analysis under uncertainty.

1. Introduction

Agricultural production takes place under conditions marked by environmental and economic uncertainties. Analyzing production activities requires appropriate tools of analysis, which themselves are subject to constant development, improvement and testing. This study investigates the potential usefulness of a novel tool for such an appraisal, the state-contingent approach to production analysis under uncertainty developed by Chambers and Quiggin (Chambers and Quiggin, 2000) and described in short in Angelova (Angelova, 2017: 22 - 26). The possible state-contingency of agricultural production is relevant, since as Shankar observes more conventional econometric methods for production analysis under uncertainty fail to account for the possibility of a non-output-cubical production technology, i.e. a technology which allows the producers to substitute potential future agricultural outcomes against one another through input allocation (Shankar, 2012: 23). A possible misspecification of the production risks might result in biased estimates.

The approach seems applicable to agricultural production under uncertainty since it described production as a process of *ex ante* committing inputs, for instance land, capital, labor and intermediate expenditures, to achieve an agricultural outcome, which itself is dependent on the occurrence of mutually exclusive states of nature or is, in

other words, state-contingent. In the context of agricultural grain production it is easy to imagine these states of nature as a set of environmental conditions, such as the presence or absence of hail, which interfere with the inputs *ex ante* committed by farmers, for instance already sown fields, in order to shape the crop yields at the end of the agricultural period.

The state-contingent approach to production and decision-making under uncertainty is fairly general. It has already been successfully applied in multiple contexts, e.g. natural resource management (Adamson et al., 2007), farm-level mathematical programming modeling for agricultural impact assessment under environmental uncertainty (Crean et al., 2013) and biodiversity conservation (Perry and Shankar, 2017), applications in the already mentioned context of agricultural production analysis under uncertainty are still numbered, possibly due to the relative novelty of the approach and the therefore limited time to address the empirical challenges posed by the implementation of any new theory.

One of the empirical challenges in the case of the state-contingent approach is the identification of the relevant states of nature and the development of environmental indicators based on values exogenous to the farmers to detect their occurrence. A study by Chavas, for instance, approaches the production problem from a dual perspective and estimates an *ex ante* cost function to check for the presence of an output

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cubical technology and thereby surpasses the direct identification of nature-states (Chavas, 2008). This approach, however, makes it necessary to simulate non-realized agricultural outputs in order to make the estimation problem tractable. Another study in this context, the investigation by Nauges, O'Donnell and Quiggin again testing for an output cubical technology, addresses the primal problem by estimating a state-contingent production function (Nauges et al., 2011). In this study, the necessity to define the nature-states in the empirical sense is exemplified, which the authors do by assuming that nature-states are synonymous with environmental conditions ex post beneficial for the cultivation of a specific crop. Their proposed method to detect the states of nature relies on asking expert opinion on what would constitute these states of nature and to subsequently evaluate data from geographically relevant weather stations.

This contribution proposes an alternative way to detect the occurrence of the so-defined nature-states for purposes of an estimation of a primal state-contingent technological formulation. An environmental indicator based on biophysical crop yield data is proposed as are two algorithms for statistical data clustering to evaluate the values of the indicator. In order to exemplify the use of the proposed indicator a state-contingent production function is estimated for the grain producing sector in the German Federal State of Saxony-Anhalt based on simulated data. For the empirical exemplification the number of states of nature is defined exogenously and the attribution of individual observations to a state of nature is achieved through a partitioning clustering algorithm. The use of a hierarchical clustering algorithm is demonstrated merely in order to exemplify a way to optimize the number of states of nature to a dataset at hand.

The paper based on Angelova (2017) is structured as follows: Section 2 presents the hierarchical and partitioning algorithms used to evaluate the values of the indicator and to detect the occurrence of nature-states. Section 3 describes the data, with Sections 3.1 and 3.2 describing the phenological and accounting observations respectively. Section 4 is devoted to data simulation, which uses the accounting observations described in Section 3.2. Section 5 introduces the proposed environmental indicator for nature-state detection, evaluates the values obtained for the indicator using the phenological observations described in Section 3.1 and assigns the yearly accounting records to one of the states of nature. Section 6 describes the functional form chosen to model the production technology and the empirical specification to be estimated. Section 7 presents the results, while Section 8 provides a discussion and concludes.

2. Methods for data clustering

Cluster analysis in general aims at grouping observations together into groups (clusters), which are simultaneously as dense within themselves and as heterogeneous between themselves as possible (Härdle and Simar, 2003: 271). As Härdle and Simar also remark, the fundamental structure of any cluster analysis involves two steps: choosing a similarity or dissimilarity measure between the observations in order to decide how alike or unlike two observations are and choosing an algorithm to construct the clusters (Härdle and Simar, 2003: 271).

The difference between hierarchical and partitioning algorithms consists in whether the cluster attribution of observations can change during the application of the algorithm (Härdle and Simar, 2003: 277). A reassignment of specific observations is possible with partitioning algorithms, such as PAM, but not with hierarchical ones.

The second type of algorithm is exemplified by the method of agglomerative hierarchical clustering, which allows the investigation of potential meaningful groupings in a dataset by successively merging all

observations into a single group starting from a partition, where each observation is in its own group. The dissimilarity (or distance) matrix between all N observations in the dataset is therefore computed. As Härdle and Simar remark the algorithm then proceeds in a two-step iterative fashion (Härdle and Simar, 2003: 277):

- The most similar clusters are merged,
- The reduced distance matrix between clusters is recomputed based on a linkage criterion.

The steps are repeated until all observations are in a single group. The appropriate number of clusters is then determined.

The way the distance between groups is defined, the linkage criterion, influences the results. A similar agglomeration result regardless of the linkage criterion is what ultimately confirms that some truth regarding the structure in the dataset is reflected, as Bartholomew et al. observe (Bartholomew et al., 2002: 21).

PAM, a partitioning algorithm, allows for the attribution of N to K groups. PAM groups observations around representative objects, or “medoids”, so that the average dissimilarity between the observations and the medoids is minimized. Kaufman and Rousseeuw formalize in the following way: if $X^{(N)}$ denotes the set of observations $x^{(n)}, n = 1, \dots, N$, and $m^{(k)}, k = 1, \dots, K$, are the K medoids, then PAM searches to determine:

$$\left\{ m^{(1)}, \dots, m^{(K)} : \sum_{i=1}^K \sum_{j=1}^N |x^{(j)} - m^{(i)}| = \min \sum_{i=1}^K \sum_{j=1}^N |x^{(j)} - x^{(i)}| \right\} \quad (1)$$

where

$$x^{(j)}, x^{(i)}, m^{(i)} \in X^{(N)}$$

The PAM algorithm is implemented in two phases: constructing the initial medoids, then improving the medoids, and thereby the cluster attribution. PAM obtains reasonable clustering results in case studies (Kaufman and Rousseeuw, 2005: 92), which analyze data structurally similar to the data used in this study.

3. Data

State-contingent crop production analysis provides a way to meaningfully integrate data from biophysical and economic origins – the biophysical data can be used to construct the environmental indicators subsequently used to properly evaluate the production circumstances based on the economic data. In this study, which primarily aim at a demonstration, data from the German Federal State of Saxony-Anhalt. The biophysical data in this study refers to crop yields generated in agronomic experiments conducted in order to obtain a benchmark for the crop yields typical of a well-managed enterprise in the region. The economic data refers to accounting record averages for enterprises selling the crop harvest, thus making heavy use of machinery, labor and intermediate inputs. The observations of both data types used span between the years 1996 to 2007. The timeframe is chosen since both biophysical and economic data were mostly available for the period.

3.1. Biophysical crop yield data

The biophysical crop yields, the mean experimental crop yields, were observed at three experimental stations in Saxony-Anhalt, whose location is marked on Map 1 in Appendix I. The analyzed crops, winter wheat and winter barley, were chosen due to data availability reasons.

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