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Measuring the impacts of production risk on technical efficiency: A state-contingent conditional order-*m* approach

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ABSTRACT

This article studies the influence of risk on farms' technical efficiency levels. The analysis extends the order-*m* efficiency scores approach proposed by Daraio and Simar (2005) to the state-contingent framework. The empirical application focuses on cross section data of Catalan specialized crop farms from the year 2011. Results suggest that accounting for production risks increases the technical performance. A 10% increase in output risk will result in a 2.5% increase in average firm technical performance.

1. Introduction

A fundamental challenge to modeling production is the design of an appropriate conceptualization of the stochastic environment in which production decisions take place. As noted in the Chavas, Chambers, & Pope, 2010 literature review of the production economics literature over the past century, production uncertainty modeling started with Day (1965) and Fuller (1965) through the use of experimental data on corn yield response to fertilizer application. This literature then evolved to the introduction of stochastic production functions that have allowed for production uncertainty mainly through additive and multiplicative structures. Recognition of the drawbacks of multiplicative and additive specifications, led Just and Pope (1978) to introduce a mean–variance model that characterizes inputs as risk increasing, neutral or decreasing, by evaluating changes in output variability as a response to input changes. Other papers based on the mean–variance or on higher order approaches, the latter allowing to study the impact of input changes on higher order moments, include Yassour, Zilberman, and Rausser (1981), Antle (1983), or Nelson and Preckel (1991).

More recently, Kumbhakar (2002) and Wang (2002) have allowed for production uncertainty in efficiency measurement. Inadequate characterization of the stochastic environment may lead to uncertainty being incorrectly attributed to efficiency and productivity differences (Chambers & Quiggin, 2000; O'Donnell et al., 2010). Skevas, Oude Lansink, and Stefanou (2012) investigate the impacts of risk on efficiency using Simar and Wilson (2007) proposal based on truncated regression and bootstrapping techniques. Risk is captured by considering the effect of climatic conditions on farmers' production environment. Results provide evidence of a dramatic increase in DEA efficiency ratings as a result of considering production uncertainty along with the dynamic impacts of pesticides on production.

In a different line of research, Chambers and Quiggin (1998) and Chambers and Quiggin (2000) propose to characterize production under uncertainty by differentiating outputs depending on the state of nature in which they are realized. This characterization leads to a stochastic technology based on a state-contingent input correspondence. The state-contingent framework is based on the Arrow–Debreu–Savage conceptualization of uncertainty in terms of a state space that allows for output substitution across states of nature. Standard stochastic production functions require non-substitutability between state-contingent outputs (Chambers & Quiggin, 2000, 2002, 2006). This restriction implies that producers can only respond to changes in the production environment by changing input use, but not reallocating state-contingent outputs. The state-contingent framework has been shown to yield more precise efficiency measures relative to approaches that impose this restriction (Chambers & Quiggin, 2006; O'Donnell et al., 2010). Serra, Chambers, and Oude Lansink (2014) have recently derived

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combined technical and environmental efficiency measures for a sample of Catalan farms. Their analysis recognizes the stochastic conditions under which production takes place by means of the state-contingent framework. Chambers, Hailu, and Quiggin (2011) approximate the stochastic technology by a state space partitioned by defining event-specific production relationships. Event-specific representations are applied to a DEA framework by using realized values of the random inputs to partition the data. Under this partition, efficiency estimates increase dramatically, thus confirming that ignoring the stochastic nature of production will lead to biased efficiency estimates.

There is ample evidence that economic agents are not neutral to risk (Antle, 1989; Bar-Shira, Just, & Zilberman, 1997; Chavas & Holt, 1990; Hennessy, 1998; Just & Pope, 2002; Saha, 1997; Serra, Zilberman, & Gil, 2008; Serra, Zilberman, Goodwin, & Featherstone, 2006). To the extent that economic decisions are influenced by risk preferences, risk implicit in the state-contingent output distribution should have an impact on the efficiency with which economic agents operate (Battese, Rambaldi, & Wan, 1997). We measure this impact through Daraio and Simar's (2005) nonparametric frontier model, that allows for the influence of external factors on firm efficiency ratings.

In frontier analysis, nonparametric efficiency measures are based upon the assumption that all observed units belong to the attainable production set. As a result, super-efficient outliers can have an influential impact on these envelopment estimators. Robustness can be increased through a trimming process that results in the frontier not enveloping all data points. Daraio and Simar (2005) provide a probabilistic formulation of a robust nonparametric order-m efficiency model, being m the trimming parameter, that allows for the influence of environmental variables that cannot be controlled by the producer, but that shape the outcome of production. Daraio and Simar (2005) proposal allows determining whether the environmental variable promotes or reduces efficiency. However, it does not adequately capture the stochastic conditions under which production takes place. The state-contingent framework proposed by Chambers and Quiggin (2000) can be implemented using standard tools of efficiency analysis when ex-ante outputs are known. As a result, we extend Daraio and Simar's (2005) framework to examine efficiency and productivity in truly state-contingent terms. The extended model is not only robust to outliers, but also to incorrect interpretations of uncertainty effects as efficiency effects.

Our empirical application focuses on cross-section data of arable farms in Catalonia, Spain. We conduct a novel production survey to elicit information from farmers on their ex-ante state-contingent outputs and overall production practices. Eliciting information on ex-ante state-contingent outputs is a highly complex process that can be subject to subjectivity regarding beliefs on the crop yield distribution and that might generate biased responses. Some respondents may provide answers in a rush or exaggerate their responses, hence the importance to use techniques that are robust to the presence of outliers.

2. Methods

Within the state-contingent framework, uncertainty is represented by a set of states of nature Ω from which nature makes a draw. Random variables in the production process can be measured as maps from the set of states Ω to the reals. Assume a single random output firm. The random output can be represented as a vector $\tilde{y} \in \mathbb{R}_+^{\Omega}$, where $\tilde{y} = \{y_s : s \in \Omega\}$, being y_s the realized (ex post) value of the random output variable $\tilde{y}$ if nature chooses state s. The non-random input vector is denoted by $x \in \mathbb{R}_+^N$. Denote by $Z \in \mathbb{Z} \subset \mathbb{R}^r$ the vector of environmental factors that are exogenous to the production process, but may explain part of it.

The stochastic production technology is represented by the set $\psi := \{(x, \tilde{y}) : x \,\text{can produce}\, \tilde{y}\}$. The boundaries of ψ are an indicator of the efficiency with which firms operate. Under the influence of environmental variables, the technology set is defined as $\psi^z := \{(x, \tilde{y}) | z : x \text{ can produce } \tilde{y}\}$. Note that for all $z \in \mathbb{Z}$, $\psi^z \subseteq \psi$. The interpretation of the technology is as follows: before knowing the realization of the state of nature, the producer chooses $(x, \tilde{y})$ from within the technology set, thus making a decision about non-stochastic inputs and stochastic outputs. After this selection has been made, nature makes a choice from $s \in \Omega$. For agricultural technologies, $s \in \Omega$ is usually related to weather conditions. It is important to note that ex-post realizations of random outputs are chosen by nature, and not by the producer (Chambers et al., 2011). Our article hypothesizes that the risk that firms face in the process from selecting the ex-ante output to obtaining ex-post realized production can have an impact on technical efficiency ratings, and we capture this risk through the environmental variable. Thus, in our particular application, $z = z(s)$.

Efficiency scores with which producers operate are usually approximated through the radial distance from each production unit to the production frontier. Along these lines, the Farrell–Debreu output-oriented efficiency score for a firm operating with $\psi := \{(x, \tilde{y}) : x \,\text{can produce}\, \tilde{y}\}$ can be defined as $\lambda(x, \tilde{y}) = \sup\{\lambda | (x, \lambda\tilde{y}) \in \psi\}$, being $\lambda(x, \tilde{y})$ the proportionate increase in outputs that can be achieved using the same technology and input combination. Since it is unknown, an estimator of the production frontier is required. Commonly used nonparametric estimators such as the Data Envelopment Analysis (DEA) initiated by Farrell (1957), or the Free Disposal Hull (FDH) proposed by Deprins, Simar, and Tulkens (1984) are based on the envelopment approach, which assumes that all observed units belong to the attainable set. Nonparametric approaches do not impose restrictive parametric structures to characterize the frontier. They however rely on various assumptions on the technology. While DEA and FDH share the postulate of free disposability, scale restrictions are imposed by DEA but not by FDH, being the latter a desirable FDH property. Convexity of the technology is a postulate of DEA, but is not imposed in FDH. Desirability of the convexity property is an open question that depends on the objective of the research (Lovell & Vanden Eeckaut, 1993).

While DEA and FDH have their own strengths and weaknesses, some scholarly papers have argued that FDH provides a better data fit than DEA (Tulkens, 1993; Vanden Eeckout, Tulkens, & Jamar, 1993). DEA techniques usually outperform FDH methods when the interest of the analysis is on the structure of the production technology. In contrast, FDH usually outperforms DEA in technical efficiency measurement, because it constructs a technology that envelops the data more closely than DEA. More specifically, FDH does not include all the points on the lines connecting the vertices of the DEA frontier. Rather, it only considers DEA vertices and the free disposal hull points interior to the vertices. This implies that while DEA mechanisms compare each firm with a hypothetical efficient frontier, FDH methods define the reference point among operating firms, which increases the credibility of the method. Also, on computational grounds, FDH involves an algorithm that yields a solution that is both very simple and efficient (Lovell & Vanden Eeckaut, 1993). Our analysis stems from the FDH technology set estimator which can be expressed as $\hat{\psi}_{FDH} := \{(x, \tilde{y}) \in \mathbb{R}_+^{N+\Omega} | \tilde{y} \le \widetilde{Y}_i, x \ge X_i i = 1, \ldots, n\}$, where $i = 1, \ldots, n$ denotes the observation number. The empirical problem consists of estimating the frontier and the efficiency scores from a random sample of production units $\chi = \{(X_i, Y_i) | i = 1, \ldots, n\}$.

Cazals, Florens, and Simar (2002) have proved that, under free disposability of inputs and outputs, a probability function of $(X, \widetilde{Y})$ on $\mathbb{R}_+^N \times \mathbb{R}_+^{\Omega}$, $H(x, \tilde{y}) = \Pr(X \le x, \widetilde{Y} \ge \tilde{y})$, can be used to characterize the production frontier. $H(x, \tilde{y})$ represents the probability of