Mark Andor[1], Frederik Hesse[2]

SETTING THE INDIVIDUAL X-FACTOR – A SYSTEMATIC COMPARISON OF DATA ENVELOPMENT ANALYSIS AND STOCHASTIC FRONTIER ANALYSIS

[1] Department of Economic Theory, University of Münster
[2] Finance Center Münster, University of Münster

ABSTRACT

Setting the individual X-factor is a core element of every incentive regulation system. The problem faced by the regulator is the choice among a wide variety of methods for setting the individual efficiency objectives. So far no single method could achieve acceptance as best-practice in both scientific research and regulatory practice. Therefore every regulation system in Europe has its own way to define the individual X-Factor. In recent years it has become common practice to use two efficiency measurement methods and to define the individual efficiency objective by using the results of both methods. The German incentive regulation of January 2009 can serve as an example. It utilizes the so called "Best-of-Four Method" to define individual X-Factors. Within this approach data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are each executed twice with two different input parameters. The highest of the four resulting efficiency estimates serves as individual X-Factor. As Andor (2009) shows that the Best-of-Four Method exhibit systematic weaknesses because it distorts the X-Factors, offers possibilities for strategic behaviour and cannot guarantee comparability of the efficiency objectives. Therefore, the final question still remains: How to optimize the determination procedure of individual efficiency objectives?

The two most popular economic approaches for the measurement of efficiency are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Thus, we are concentrating on these methods in this study. DEA is a linear programming model, originally introduced by Charnes et al. (1978) and extended by Banker et al. (1984) for variable returns to scale. DEA develops an empirical frontier function whose shape is determined by the most efficient producers of the observed data set. Efficiency is measured as the distance to the frontier. The main advantage of this approach is its nonparametric nature. SFA, developed by Aigner et al. (1977) and Meeusen et al. (1977), is a regression-based approach which integrates two unobserved error terms representing efficiency and statistical noise. Assuming a production function and specific distributions for the error terms allows estimation via maximum likelihood method. The advantage here is the ability to measure efficiency while considering the presence of statistical noise.

The regulator is facing the problem that the "true" efficiency is unknown. Only input and output are observable. In order to overcome this problem, we elude using empirical data by generating our own dataset. Accordingly, we possess as well the true efficiency values as the efficiency estimates of both methods. Within productivity analysis literature Monte Carlo Simulations are frequently used (e. g. Banker et al. (1993), Yu (1998), Perelman/Satin (2009), Adler/Yazhemsky (2010)), but literature lacks an exhaustive systematic simulation comparison between DEA and SFA.

Our simulation study is intended to close this research gap by comparing DEA and SFA regarding their ability to provide reliable efficiency estimates and rankings. In analogy to Jensen (2005), who compare the corrected ordinary least squares method and SFA, the simulation design covers the quantification of the influence of:

1. different sample sizes,
2. different ratios of the error and inefficiency terms,
3. different inefficiency distributions,
4. missing variables and
5. different functional forms.

Assuming that a combination of the estimates is most suitable to set X-Factors realistically, the regulator needs to know which combination to compute. As there are many different possibilities the regulator can choose from (e. g. the best-of-two-method or the mean), we analyze this problem in a second step to give a well-founded political implication for setting individual X-Factors. Based on this extensive simulation study we are finally able to identify the best performing approach. This can be seen as the next step towards finding the best-practice for setting individual X-Factors in incentive regulation systems.