New Developments in Benchmarking Techniques

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BNetzA Conference Efficiency Benchmarking
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Agenda

- Overview of Efficiency Benchmarking Techniques
- "Targeted" Monte Carlo Simulations: the "Statistical Referee"

Overview of Efficiency Benchmarking Techniques

Regression Techniques/Methods

- There are a host of efficiency estimation methods beyond what is currently being used
- For SFA and DEA, there are many elaborate variants
  - nonparametric SFA
  - stochastic DEA
- Robust estimation of SFA/DEA ($\rightarrow outliers$)

Regression Techniques/Methods

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- For SFA and DEA, there are many elaborate variants
  - nonparametric SFA
  - stochastic DEA
- Robust estimation of SFA/DEA ($\rightarrow outliers$)

Regression Techniques/Methods

- Large body of literature in SFA that focuses on nonparametric estimation of 'parts' of the model
  - Fan, Li & Weersink (1996)
  - Kumbhakar, Park, Simar & Tsionas (2007)
  - Tran & Tsionas (2009)
  - Martins-Filho & Yao (2015)
  - Simar, Van Keilegom & Zelenyuk (2017)
  - Parmeter, Wang & Kumbhakar (2017)
  - Florens, Simar & Van Keilegom (2020)
  - Zhou, Parmeter & Kumbhakar (2020)

Regression Techniques/Methods

- ... and DEA literature that aims to consider statistical noise
  - Kneip, Simar & Wilson (2008)
  - Simar & Zelenyuk (2011)
  - Kuosmanen & Kortelainen (2012)
  - Daouia, Noh & Park (2016)

Regression Techniques / Methods

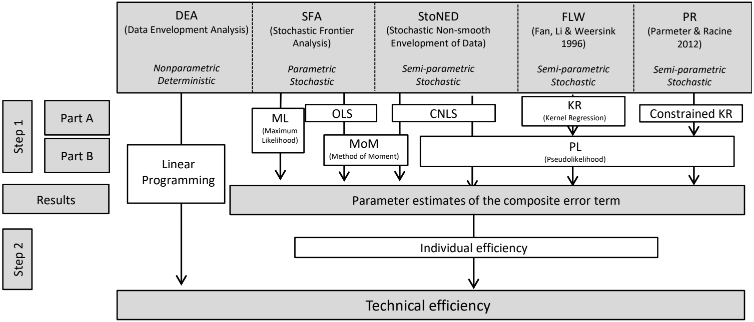
- Comparisons of (some of) these elaborate methods, e.g. in
  - Badunenko et al. (2012),
  - Andor & Hesse (2014) and
  - Parmeter & Zelenyuk (2019)

Regression Techniques / Methods

- For robust estimation, we have
- DEA:
  - order-m (Cazals et al. 2002) and
  - order-α frontiers (Aragon et al. 2005) in DEA (VRS and CRS)
- SFA:
  - Song, Oh & Kang (2017): uses MDPD (Minimum Density Power Divergence)
  - Horrace & Parmeter (2018): Laplace-Exponential
  - Wheat, Stead & Greene (2019): t-Half-t distributional specification

Regression Techniques / Methods

Overview of some methods to develop a rough understanding



- Newer methods: semi-parametric
- Yet, also "second-step problem"

“Targeted” Monte Carlo Simulation: the “Statistical Referee”

“Targeted” Monte Carlo Simulations

- Basics
- Some Examples
- Practical guidance: What could be done?

Monte Carlo Simulations – Basics

- MC simulations: "statistical referee" in order to
  - compare methods
  - determine influencing factors
  - estimate the strength of influencing factors
- MC simulations:
  - Generation of own data sets: "true" efficiency can be compared with estimated efficiency
  - For this, the data generation process (DGP) has to be defined
  - Variation of the DGP to identify influencing factors
  - Replication to ensure robustness of results

Data generation process (DGP) in MC simulations

$$q_j = \underbrace{F(z_{i,j})}_{Production\ Function} \cdot \underbrace{exp^{(\varepsilon_j)}}_{Composed\ error\ term} \quad \text{with } \varepsilon_j = v_j - u_j \text{ and } j = 1, ..., n, \tag{1}$$

For example, the DGP must specify:

- Functional form of the production function
- Distribution of inputs
- Distribution of the inefficiency and disturbance term
- Number of enterprises (e.g. DSOs)

Monte Carlo Simulations – Example 1

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Decision Support

Combining uncertainty with uncertainty to get certainty? Efficiency analysis for regulation purposes

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A B S T R A C T

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA), as well as combinations thereof, are widely applied in incentive regulation practice, where the assessment of efficiency plays a major role in regulation design and benchmarking. Using a Monte Carlo simulation experiment, this paper compares the performance of six alternative methods commonly applied by regulators. Our results demonstrate that combination approaches, such as taking the maximum or the mean over DEA and SFA efficiency scores, have certain practical merits and might offer a useful alternative to strict reliance on a singular method. In particular, the results highlight that taking the maximum not only minimizes the risk of underestimation, but can also improve the precision of efficiency estimation. Based on our results, we give recommendations for the estimation of individual efficiencies for regulation purposes and beyond.

1. Introduction

Over the past three decades, many countries have introduced regulatory reforms and incentive regulation in network sectors like electricity, gas, telecommunications, and water. Although concrete regulation designs may vary fundamentally, in many incentive-based regulation schemes, efficiency estimation methods play a major role (see, for example, Bogetoft & Otto, 2010; Coelli & Lawrence, 2006; Haney & Pollitt, 2009). These methods are used to benchmark regulated firms and account for firm-specific efficiency estimates in the regulatory design. If the current efficiency level of a firm was not considered in the regulation process, incentive-based regulation schemes would favor firms that are less efficient at the beginning of the regulation period. After estimating the efficiency of the firms, each regulated firm obtains an individual efficiency improvement target, the so-called X-factor, with the aim of decreasing its inefficiency through the end of the regulation period (e.g. Nykamp, Andor, & Hurink, 2012). Usually, the firm-specific X-factors enable firms to earn a fair rate of return on capital if they achieve the efficient cost level that is defined by the regulatory authority (Coelli, Estache, Perelman, and Trujillo, 2003, p. 8).

Thus, estimated efficiency scores have a substantial financial impact on regulated firms and the choice of the estimation method is of major relevance, as it often heavily influences the estimated level of (in)efficiency. Nevertheless, both the theoretical literature as well as regulation practice have not yet found the "best" strategy for determining individual efficiency targets. Consequently, regulators have used a broad array of concepts to determine the individual X-factor. In the energy sector for example, many regulating authorities estimate firm level efficiency by adopting either (I) data envelopment analysis (DEA, Charnes, Cooper, & Rhodes, 1978), which is quite flexible and whose frontier is only restricted via its axiomatic foundation[1], but estimates efficiency without considering statistical noise[2], (II) parametric stochastic frontier analysis (SFA, Aigner, Lovell, & Schmidt, 1977; Meeusen & van Den Broeck, 1977), which takes statistical noise into account, but typically requires assumptions concerning the functional form of the frontier as well as the distribution of inefficiency or (III) a combination of the estimates of these two (see also Banker, Førsund, & Zhang, 2017).

Aside from the direct application of individual estimation methods, for example DEA being deployed to benchmark in Norway, regulation authorities have recently begun to apply combination

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[1] The axioms are convexity, inefficiency ("free disposability"), ray unboundedness, and minimum extrapolation (Banker, Charnes, & Cooper, 1984; Fried, Lovell, & Schmidt, 2008).

[2] Several extensions to the original DEA model have been proposed in the literature to account for statistical noise, such as stochastic DEA (Simar & Zelenyuk, 2011) or extended versions of the Benefit-of-the-Doubt-method (see, for an introduction, Cherchye, Moesen, Rogge, & Van Puyenbroeck, 2007), for example the robust order-m model (Cazals, Florens, & Simar, 2002).

Monte Carlo Simulations – Example 1

Monte Carlo simulation based on real data

Table 2
Descriptive statistics of Finnish electricity distribution companies.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Entire data set					
Total cost in EUR 1000	8418.9	18047.8	267.8	3102.2	117554.1
Energy transmission in gigawatt hours	480.4	971.5	14.8	171.3	6599.7
Length of network in kilometers	4135.3	10223.3	50.8	988.6	67611.1
No. of customers	35448.7	71870.7	24.3	11081.3	420473.0
Final data set used for the simulation					
Total cost in EUR 1000	12750.5	23243.2	1588.8	5458.5	117554.1
Energy transmission in gigawatt hours	683.4	1180.0	94.9	305.3	6599.7
Length of network in kilometers	6881.6	13673.9	340.1	2656.3	67611.1
No. of customers	50107.3	82521.9	5146.3	21987.4	420473.0

Source: Finnish Energy Market Authority (Energiamarkkinavirasto, EMV), www.emvi.fi

Source: Andor et al. (2019)

Monte Carlo Simulations – Example 1

Table 3
Overview of cases and scenarios.

Case	σ_v	Distribution of u	True cost function	σ_u	Sample size n
1 "SFA-CD"	0.01, 0.05	$N_+(0, \sigma_u^2)$	CD	0.01, 0.05, 0.15	50, 100, 200, 400, 800
2	0	$N_+(0, \sigma_u^2)$	CD	0.01, 0.05, 0.15	50, 100, 200, 400, 800
3	0.01, 0.05	$\Gamma(1, \sigma_u)$	CD	0.01, 0.05, 0.15	50, 100, 200, 400, 800
4	0	$\Gamma(1, \sigma_u)$	CD	0.01, 0.05, 0.15	50, 100, 200, 400, 800
5	0.01, 0.05	$N_+(0, \sigma_u^2)$	TL	0.01, 0.05, 0.15	50, 100, 200, 400, 800
6	0	$N_+(0, \sigma_u^2)$	TL	0.01, 0.05, 0.15	50, 100, 200, 400, 800
7 "SFA-TL"	0.01, 0.05	$\Gamma(1, \sigma_u)$	TL	0.01, 0.05, 0.15	50, 100, 200, 400, 800
8	0	$\Gamma(1, \sigma_u)$	TL	0.01, 0.05, 0.15	50, 100, 200, 400, 800
9	0.01, 0.05	$N_+(0, \sigma_u^2)$	TL + DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
10	0	$N_+(0, \sigma_u^2)$	TL + DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
11 "TL-DEA"	0.01, 0.05	$\Gamma(1, \sigma_u)$	TL + DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
12	0	$\Gamma(1, \sigma_u)$	TL + DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
13	0.01, 0.05	$N_+(0, \sigma_u^2)$	DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
14	0	$N_+(0, \sigma_u^2$	DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
15	0.01, 0.05	$\Gamma(1, \sigma_u)$	DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800
16 "DEA"	0	$\Gamma(1, \sigma_u)$	DEA	0.01, 0.05, 0.15	50, 100, 200, 400, 800

Source: Andor et al. (2019)

Monte Carlo Simulations – Example 1

Evaluation: "Oldies" and combination approaches

Table 4
Overall performance of the six methods.

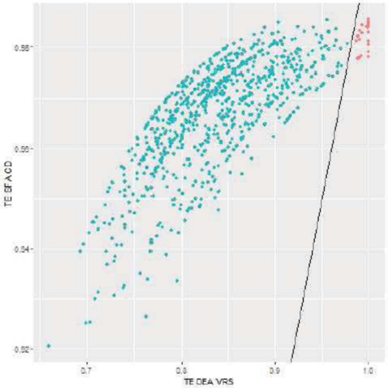
Scenarios	Performance measure	Estimation method					
		SFA-CD	SFA-TL	DEA-CRS	DEA-VRS	AM	MAX
I All	RMSE	0.0795	0.0303	0.0821	0.0503	0.0519	0.0215
	Bias	−0.0531	−0.0064	−0.0553	−0.0057	−0.0337	0.0052
	PU	0.8500	0.7000	0.8350	0.5950	0.9300	0.3150
II No Noise	RMSE	0.0793	0.0195	0.0626	0.0203	0.0383	0.0142
	Bias	−0.0526	−0.0032	−0.0399	0.0032	−0.0276	0.0084
	PU	0.8400	0.6700	0.7012	0.2150	0.9250	0.0775
III With Noise	RMSE	0.0796	0.0348	0.0942	0.0586	0.0585	0.0267
	Bias	−0.0534	−0.0081	−0.0668	−0.0180	−0.0399	0.0025
	PU	0.8550	0.7200	0.8800	0.7200	0.9325	0.4650

Note: RMSE = Root mean square error, PU = Percentage of underestimated firms.

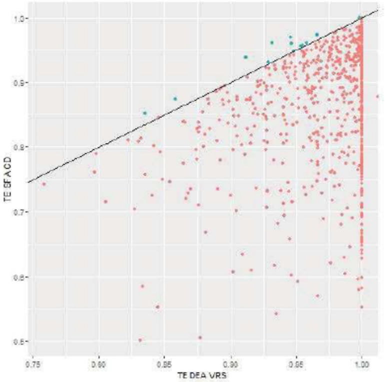
Source: Andor et al. (2019)

Monte Carlo Simulations – Example 1

Exemplary comparison: estimates from DEA-VRS and SFA-CD



(a) Case 1 (“SFA-CD”)



(d) Case 16 (“DEA”)

Source: Andor et al. (2019)

Monte Carlo Simulations – Example 2

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The StoNED age: the departure into a new era of efficiency analysis? A monte carlo comparison of StoNED and the “oldies” (SFA and DEA)

Mark Andor · Frederik Hesse

Published online: 4 July 2013

Abstract Based on the seminal paper of Farrell (J R Stat Soc Ser A (General) 120(3):253–290, 1957), researchers have developed several methods for measuring efficiency. Nowadays, the most prominent representatives are nonparametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA), both introduced in the late 1970s. Researchers have been attempting to develop a method which combines the virtues—both nonparametric and stochastic—of these “oldies”. The recently introduced Stochastic non-smooth envelopment of data (StoNED) by Kuosmanen and Kortelainen (J Prod Anal 38(1):11–28, 2012) is such a promising method. This paper compares the StoNED method with the two “oldies” DEA and SFA and extends the initial Monte Carlo simulation of Kuosmanen and Kortelainen (J Prod Anal 38(1):11–28, 2012) in several directions. We show, among others, that, in scenarios without noise, the rivalry is still between the “oldies”, while in noisy scenarios, the nonparametric StoNED PL now constitutes a promising alternative to the SFA ML.

Keywords Efficiency · Stochastic non-smooth envelopment of data (StoNED) · Data envelopment analysis (DEA) · Stochastic frontier analysis (SFA) · Monte carlo simulation

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1 Introduction

In his classic paper, Farrell (1957) stated that measuring the efficiency of productivity is important to economic theorists and economic policy makers alike. Based on Farrell’s work, researchers have developed several methods for measuring efficiency. Despite this progress, after more than five decades of efficiency analysis research, there is still no single superior method (see, among others, Resti 2000; Mortimer 2002; Badunenko et al. 2012).

The efficiency analysis literature can be divided into two main branches of parametric and nonparametric methods. Data envelopment analysis (DEA) is the most popular representative of the nonparametric methods. It is a linear programming method which constructs a nonparametric envelopment frontier over the data points. Despite the fact that previous papers also proposed mathematical programming methods (see, for example, Afriat 1972), DEA is generally attributed to Charnes et al. (1978). DEA estimates efficiency without considering statistical noise and is thus a deterministic method. This is its main disadvantage. On the other hand, its main advantage is flexibility, due to its nonparametric nature.

In contrast, parametric methods require an assumption about the functional form of the production function. The corrected ordinary least squares method (COLS), originally proposed by Winsten (1957), estimates the efficient frontier by shifting the ordinary least squares regression towards the most efficient producer. Subsequently, it measures inefficiency as the distance to this frontier. COLS has the same disadvantage as DEA, since it is also deterministic. Aigner et al. (1977) and Meeusen and van den Broeck (1977) developed a stochastic parametric model, called

Monte Carlo Simulations – Example 2

Comparison DEA, SFA and StoNED

Table 2 Overview of the performance criteria for all 188 settings

	DEA	SFA MoM	SFA ML	StoNED MoM	StoNED PL
MD	−0.0696	−0.0496	−0.0230	−0.0385	0.0295
MAD	0.1101	0.0850	0.0659	0.0862	0.0719
Rank (MAD)	*3.63*	*3.31*	*2.14*	*3.49*	*2.42*
MSE	0.0262	0.0124	0.0106	0.0132	0.0106
Rank (MSE)	*3.58*	*3.23*	*2.15*	*3.56*	*2.49*
MRC	0.6868	0.7163	0.7295	0.6613	
Rank (MRC)	*3.21*	*1.98*	*1.36*	*3.46*	

Source: Andor & Hesse (2014)

Comparison DEA, SFA and StoNED

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Table 3 Overview of the performance criteria in the subsample without noise ($\rho_{nts} = 0$)

	DEA	SFA MoM	SFA ML	StoNED MoM	StoNED PL
MD	0.0127	−0.0530	−0.0023	−0.0368	0.0227
MAD	0.0426	0.0682	0.0232	0.0701	0.0535
Rank (MAD)	*2.33*	*4.01*	*1.30*	*4.06*	*3.31*
MSE	0.0051	0.0074	0.0023	0.0084	0.0066
Rank (MSE)	*2.31*	*3.80*	*1.39*	*4.19*	*3.34*
MRC	0.8710	0.9001	0.9290	0.8268	
Rank (MRC)	*2.84*	*2.30*	*1.23*	*3.64*	

Source: Andor & Hesse (2014)

Monte Carlo Simulations – Example 2

Comparison DEA, SFA and StoNED

Table 4 Overview of the performance criteria in the subsample with noise ($\rho_{nts} > 0$)

	DEA	SFA MoM	SFA ML	StoNED MoM	StoNED PL
MD	−0.1282	−0.0455	−0.0339	−0.0385	0.0373
MAD	0.1570	0.0960	0.0940	0.0967	0.0838
Rank (MAD)	*4.61*	*2.84*	*2.62*	*3.18*	*1.75*
MSE	0.0400	0.0155	0.0152	0.0161	0.0131
Rank (MSE)	*4.53*	*2.87*	*2.54*	*3.22*	*1.85*
MRC	0.5571	0.5892	0.5903	0.5474	
Rank (MRC)	*3.53*	*1.70*	*1.45*	*3.32*	

Source: Andor & Hesse (2014)

Monte Carlo Simulations – Example 2

Comparison DEA, SFA and StoNED

- StoNED relatively good
- StoNED particularly good when "noise" is present in the data

Monte Carlo Simulations – Example 2

Impact of the factor "sample" on estimation accuracy (MAD)

Table 5 Variation of sample size

Method	NTS	0			1		
	PF	PF I	PF II	PF III	PF I	PF II	PF III
DEA	DMU = 20	0.0539	0.0545	0.0551	0.1209	0.1055	0.1354
	DMU = 50	0.0314	0.0357	0.0373	0.1384	0.1335	0.1544
	DMU = 100	0.0206	0.0232	0.0326	0.1729	0.1648	0.1960
	DMU = 200	0.0127	0.0170	0.0319	0.1985	0.1814	0.2210
SFA MOM	DMU = 20	0.0569	0.0634	0.0621	0.0952	0.1004	0.0940
	DMU = 50	0.0688	0.0697	0.0755	0.0917	0.1032	0.0976
	DMU = 100	0.0791	0.0737	0.0811	0.0987	0.1034	0.0896
	DMU = 200	0.0838	0.0832	0.0771	0.1029	0.1086	0.0997
SFA ML	DMU = 20	0.0279	0.0422	0.0273	0.1135	0.1182	0.1080
	DMU = 50	0.0101	0.0344	0.0130	0.0949	0.1006	0.0960
	DMU = 100	0.0053	0.0332	0.0119	0.0907	0.0912	0.0894
	DMU = 200	0.0024	0.0315	0.0114	0.0866	0.0939	0.0868
STONED MOM	DMU = 20	0.0610	0.0665	0.0684	0.1018	0.0923	0.0951
	DMU = 50	0.0676	0.0634	0.0740	0.0906	0.1029	0.1011
	DMU = 100	0.0734	0.0674	0.0799	0.0980	0.1021	0.0900
	DMU = 200	0.0823	0.0798	0.0774	0.0965	0.1015	0.0994
STONED PL	DMU = 20	0.0658	0.0642	0.0710	0.0986	0.0930	0.0900
	DMU = 50	0.0466	0.0467	0.0509	0.0809	0.0814	0.0862
	DMU = 100	0.0378	0.0368	0.0414	0.0749	0.0765	0.0776
	DMU = 200	0.0376	0.0644	0.0520	0.0931	0.0851	0.0950

Performance criterion: Mean absolute deviation (MAD). DGP: *Sample size*: DMU= 20, 50, 100, 200; *Error term*: Noise-to-signal ratio (NTS): 0 and 1; $u_j \sim$ Exp(μ=1/6); Heteroscedasticity: NO; *Production function*: PF I (Cobb Douglas with increasing returns to scale), PF II (CRESH), PF III (Translog); Collinearity: 0; Input distribution: $z_j \sim$ U(5,15); Number of inputs(z): m = 2

Impact of the factor "noise" on estimation accuracy (MAD)

Table 6 Variation of noise-to-signal ratio

Method	DMU	50			100		
	PF	PF I	PF II	PF III	PF I	PF II	PF III
DEA	NTS = 0	0.0314	0.0357	0.0373	0.0206	0.0232	0.0326
	NTS = 0.5	0.0650	0.0607	0.0815	0.0728	0.0674	0.0952
	NTS = 1	0.1384	0.1335	0.1544	0.1729	0.1648	0.1960
	NTS = 2	0.2908	0.3050	0.3247	0.3480	0.3331	0.3586
SFA MoM	NTS = 0	0.0688	0.0697	0.0755	0.0791	0.0737	0.0811
	NTS = 0.5	0.0799	0.0832	0.0883	0.0900	0.0881	0.0813
	NTS = 1	0.0917	0.1032	0.0976	0.0987	0.1034	0.0896
	NTS = 2	0.1240	0.1255	0.1240	0.1153	0.1260	0.1311
SFA ML	NTS = 0	0.0101	0.0344	0.0130	0.0053	0.0332	0.0119
	NTS = 0.5	0.0623	0.0663	0.0617	0.0587	0.0642	0.0585
	NTS = 1	0.0949	0.1006	0.0960	0.0907	0.0912	0.0894
	NTS = 2	0.1427	0.1516	0.1501	0.1313	0.1444	0.1400
StoNED MoM	NTS = 0	0.0676	0.0634	0.0740	0.0734	0.0674	0.0799
	NTS = 0.5	0.0806	0.0791	0.0885	0.0894	0.0986	0.0826
	NTS = 1	0.0906	0.1029	0.1011	0.0980	0.1021	0.0900
	NTS = 2	0.1289	0.1279	0.1282	0.1208	0.1258	0.1348
StoNED PL	NTS = 0	0.0466	0.0467	0.0509	0.0378	0.0368	0.0414
	NTS = 0.5	0.0652	0.0636	0.0649	0.0580	0.0593	0.0587
	NTS = 1	0.0809	0.0814	0.0862	0.0749	0.0765	0.0776
	NTS = 2	0.1050	0.1100	0.1118	0.1036	0.1048	0.1048

Performance criterion: Mean absolute deviation (MAD). DGP: DMU = 50, 100; *Error term*: Noise-to-signal ratio (NTS): 0, 0.5, 1 and 2; $u_j \sim$ Exp(μ = 1/6); Heteroscedasticity: NO; *Production function*: PF I (Cobb Douglas with increasing returns to scale), PF II (CRESH), PF III (Translog); Collinearity: 0; Input distribution: $z_j \sim$ U(5,15); Number of inputs(z): m = 2

Monte Carlo Simulations – Example 3

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'Standard' incentive regulation hinders the integration of renewable energy generation

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HIGHLIGHTS

- We measure the influence of investments on efficiency by applying DEA and SFA.
- We compare the profitability of alternative investments under incentive regulation.
- Incentive regulation gives incentives to refuse investment at all.
- If DSOs are forced to invest, reinforcement is preferable to smart solutions.
- Ways to consider innovation in incentive regulations are required and discussed.

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ABSTRACT

The connection and distribution of growing, decentralized electricity generation from renewable energy sources (RES-E) is leading to massive investment needs. Besides investing in additional 'conventional' assets (e.g. cables), grid operators can also invest in innovative 'smart solutions' like local storage capacities or voltage regulation appliances, which may be a more suitable way of integrating RES-E. This paper investigates the influence of incentive regulation on the investment decision of grid operators to integrate RES-E. We describe the technical and regulatory background, explain the advantages of 'smart solutions' and present an approach for comparing investment scenarios. As an example, we calculate the profitability of investments in a case study of the German electricity market. We apply Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to show the influence of the investment alternatives on grid operator efficiency objectives. We demonstrate that under current 'standard' incentive regulation, the grid operators gain profitability by avoiding investments and – if they are forced to invest – by not implementing 'smart solutions'. The results highlight the need to consider innovation in the regulation design. Further research should investigate specific instruments that can be used to account for innovation. Our brief discussion of such instruments provides a starting point.

1. Introduction

In the last few years, the growth of electricity generation from ... Germany, for example, the Photovoltaic (PV) capacity increased, due to new installations, from 9.9 GW up to 17.3 GW (+74%) in 2010. The number of wind and biomass installations also rose

Monte Carlo Simulations – Example 3

Uncovering problems of regulation:

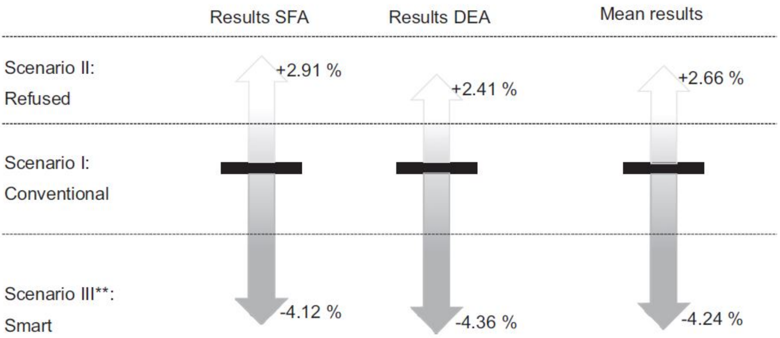

Fig. 7. Average influence of investment alternatives on efficiency values.

Source: Nykamp et al. (2012)

Influence of different investment scenarios on efficiency values: Lack of innovation incentives (in 2011)

Monte Carlo Simulations – What can be done?

Monte Carlo Simulations - A Tool for Practice

MC simulations can be built purely theoretically, but also based on empirical data.

MC simulations can be a helpful tool, for example to:

- Increase the understanding of the methods
- Determine the influence of certain factors
- Illustrate problems of regulation
- Improve model selection

How to choose the benchmarking technique?

My approach would be the following

- Discuss and decide all "circumstances" and objectives
- Comprehensive search for potential methods and approaches (including combination approaches, such as Best-of, average, weighted...)
- Conducting a thorough Monte Carlo study: "Horse race"
- Identify the best approach for "your" purposes

Thank you

- Mark A. Andor (mark.andor@rwi-essen.de)

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Monte Carlo Simulations – What can be done?

Model Selection

- What assumptions should we make?
  - How does the production function look like?
  - Which inputs?
  - What are the "best" assumptions for the inefficiency and the noise term?
  - ...

Underlying question: what is the best way to estimate the "true" efficiency values?

Monte Carlo Simulations – What can be done?

Model Selection

- So what is the best way to estimate the "true" efficiency values?
- Bad news: nobody knows for sure
- Standard procedure: using statistical indicators based on the empirical estimations
- While useful, there are certainly several limitations (some already discussed)
- Alternative or complement: **"Targeted" MC simulations**

Monte Carlo Simulations – What can be done?

What can be done?

- MC simulations based on empirical data
- “Targeted” on the German gas market: e.g., sample size fixed
- Thinking about main questions
- Determine and vary the DGP
- Vary the assumptions in the estimations
- Compare the performance
- You can learn a lot

Monte Carlo Simulations – What can be done?

Questions that could be answered, for example:

- Let us check what happens with the estimates if an assumption is wrong
- Let us check what happens when we adapt the assumptions in the estimation
- What are the major "problems" / "challenges"?
- What is less important?

Monte Carlo Simulations – What can be done?

Potential insights, for example:

- Identify and provide evidence that some assumptions are not crucial
- Identify methods/assumptions that perform better on average across several reasonable assumptions...
- ...or in other words, which are less influenced by certain assumptions/are more flexible
- Effects/Insights can be nicely illustrated

Monte Carlo Simulations – Example 3

Example: Assumption about the inefficiency term distribution

Table 8 Variation of the distribution of the inefficiency term

Method	NTS	0					
	DMU	50			100		
	PF	PF I	PF II	PF III	PF I	PF II	PF III
DEA	$u_i \sim HN\ (\mu = 1/6)$	0.0411	0.0450	0.0407	0.0262	0.0307	0.0344
	$u_i \sim Exp\ (\mu = 1/6)$	0.0314	0.0357	0.0373	0.0206	0.0232	0.0326
SFA MoM	$u_i \sim HN\ (\mu = 1/6)$	0.0309	0.0422	0.0339	0.0248	0.0385	0.0259
	$u_i \sim Exp\ (\mu = 1/6)$	0.0688	0.0697	0.0755	0.0791	0.0737	0.0811
SFA ML	$u_i \sim HN\ (\mu = 1/6)$	0.0170	0.0338	0.0150	0.0084	0.0326	0.0127
	$u_i \sim Exp\ (\mu = 1/6)$	0.0101	0.0344	0.0130	0.0053	0.0332	0.0119
StoNED MoM	$u_i \sim HN\ (\mu = 1/6)$	0.0396	0.0409	0.0438	0.0315	0.0303	0.0354
	$u_i \sim Exp\ (\mu = 1/6)$	0.0676	0.0634	0.0740	0.0734	0.0674	0.0799
StoNED PL	$u_i \sim HN\ (\mu = 1/6)$	0.0623	0.0618	0.0579	0.0463	0.0448	0.0554
	$u_i \sim Exp\ (\mu = 1/6)$	0.0466	0.0467	0.0509	0.0378	0.0368	0.0414

Performance criterion: Mean absolute deviation (MAD). DGP: DMU = 50, 100; *Error term*: Noise-to-signal ratio (N
NO; *Production function*: PF I (Cobb Douglas with increasing returns to scale), PF II (CRESH), PF III (Translog); Collir

Source: Andor & Hesse (2014)

Monte Carlo Simulations – Example 3

Example: Assumption about the production function

Table 11 Variation of the functional form of the production function

Method	NTS	0		1	
	DMU	50	100	50	100
DEA	PF I Cobb-Douglas (IRS)	0.0314	0.0206	0.1384	0.1729
	PF I.B Cobb-Douglas (CRS)	0.0330	0.0220	0.1273	0.1642
	PF I.C Cobb-Douglas (DRS)	0.0354	0.0217	0.1326	0.1566
	PF II CRESH (Inputsub. = 0.33)	0.0357	0.0232	0.1335	0.1648
	PF II.B CRESH (Inputsub. = 1.33)	0.0349	0.0216	0.1317	0.1587
	PF II.C CRESH (Inputsub. = 3)	0.0317	0.0201	0.1406	0.1658
	PF III Translog	0.0373	0.0326	0.1544	0.1960
SFA MoM	PF I Cobb-Douglas (IRS)	0.0688	0.0791	0.0917	0.0987
	PF I.B Cobb-Douglas (CRS)	0.0743	0.0719	0.0990	0.0972
	PF I.C Cobb-Douglas (DRS)	0.0617	0.0787	0.0933	0.0967
	PF II CRESH (Inputsub. = 0.33)	0.0697	0.0737	0.1032	0.1034
	PF II.B CRESH (Inputsub. = 1.33)	0.0599	0.0692	0.0996	0.1035
	PF II.C CRESH (Inputsub. = 3)	0.0753	0.0761	0.1061	0.1020
	PF III Translog	0.0755	0.0811	0.0976	0.0896
SFA ML	PF I Cobb-Douglas (IRS)	0.0101	0.0053	0.0949	0.0907
	PF I.B Cobb-Douglas (CRS)	0.0094	0.0046	0.1018	0.0902
	PF I.C Cobb-Douglas (DRS)	0.0091	0.0046	0.0985	0.0905
	PF II CRESH (Inputsub. = 0.33)	0.0344	0.0332	0.1006	0.0912
	PF II.B CRESH (Inputsub. = 1.33)	0.0113	0.0078	0.0972	0.0950
	PF II.C CRESH (Inputsub. = 3)	0.0186	0.0176	0.1024	0.0910
	PF III Translog	0.0130	0.0119	0.0960	0.0894
StoNED MoM	PF I Cobb-Douglas (IRS)	0.0676	0.0734	0.0906	0.0980
	PF I.B Cobb-Douglas (CRS)	0.0730	0.0693	0.1139	0.0966
	PF I.C Cobb-Douglas (DRS)	0.0608	0.0756	0.0941	0.0968
	PF II CRESH (Inputsub. = 0.33)	0.0634	0.0674	0.1029	0.1021
	PF II.B CRESH (Inputsub. = 1.33)	0.0597	0.0678	0.1019	0.1036
	PF II.C CRESH (Inputsub. = 3)	0.0749	0.0735	0.1005	0.1009
	PF III Translog	0.0740	0.0799	0.1011	0.0900
StoNED PL	PF I Cobb-Douglas (IRS)	0.0466	0.0378	0.0809	0.0749
	PF I.B Cobb-Douglas (CRS)	0.0454	0.0361	0.0883	0.0778
	PF I.C Cobb-Douglas (DRS)	0.0443	0.0369	0.0788	0.0761
	PF II CRESH (Inputsub. = 0.33)	0.0467	0.0368	0.0814	0.0765
	PF II.B CRESH (Inputsub. = 1.33)	0.0471	0.0366	0.0831	0.0748
	PF II.C CRESH (Inputsub. = 3)	0.0442	0.0355	0.0819	0.0795
	PF III Translog	0.0509	0.0414	0.0862	0.0776

Performance criterion: Mean absolute deviation (MAD). DGP: DMU = 50, 100; *Error term*: Noise-to-signal ratio (NTS): 0 and 1; $u_j \sim \text{Exp}(\mu = 1/6)$; Heteroscedasticity: NO; *Production function*: See Table 10; Collinearity: 0; Input distribution: $z_j \sim U(5,15)$; Number of inputs(z): m = 2

Source: Andor & Hesse (2014)

Example: Assumption about the production function

Table 10 Parametrization of the production functions

PF	Description	Parametrization
I	Cobb-Douglas, IRS	$\beta_1 = \beta_2 = 0.6$
I.B	Cobb-Douglas, CRS	$\beta_1 = \beta_2 = 0.5$
I.C	Cobb-Douglas, DRS	$\beta_1 = \beta_2 = 0.4$
II	CRESH (Inputsubstitution = 0.33)	$\rho = \rho_i = 2$
II.B	CRESH (Inputsubstitution = 1.33)	$\rho = \rho_i = -0.25$
II.C	CRESH (Inputsubstitution = 3)	$\rho = \rho_i = -0.67$
III	Translog	$\beta_0 = 1, \beta_1 = \beta_2 = 0.3, \beta_{11} = \beta_{22} = \beta_{12} = \beta_{21} = 0.1$

Source: Andor & Hesse (2014)

Monte Carlo Simulations – Example 3

Example: Number of inputs

Table 12 Variation of the number of inputs

Method	NTS	0		1	
	DMU	50	100	50	100
DEA	PF I.1 (1 Input)	0.0139	0.0108	0.1716	0.2087
	PF I.2 (2 Inputs)	0.0314	0.0206	0.1384	0.1729
	PF I.3 (3 Inputs)	0.0547	0.0406	0.1234	0.1409
	PF I.4 (4 Inputs)	0.0704	0.0588	0.1065	0.1231
SFA MoM	PF I.1 (1 Input)	0.0585	0.0679	0.1081	0.1103
	PF I.2 (2 Inputs)	0.0688	0.0791	0.0917	0.0987
	PF I.3 (3 Inputs)	0.0623	0.0674	0.0908	0.0943
	PF I.4 (4 Inputs)	0.0606	0.0598	0.0962	0.1035
SFA ML	PF I.1 (1 Input)	0.0066	0.0036	0.1012	0.0973
	PF I.2 (2 Inputs)	0.0101	0.0053	0.0949	0.0907
	PF I.3 (3 Inputs)	0.0138	0.0061	0.1050	0.0939
	PF I.4 (4 Inputs)	0.0150	0.0082	0.1052	0.0958
StoNED MoM	PF I.1 (1 Input)	0.0619	0.0686	0.1095	0.1107
	PF I.2 (2 Inputs)	0.0676	0.0734	0.0906	0.0980
	PF I.3 (3 Inputs)	0.0635	0.0674	0.0919	0.0940
	PF I.4 (4 Inputs)	0.0922	0.0854	0.1019	0.1046
StoNED PL	PF I.1 (1 Input)	0.0313	0.0272	0.0803	0.0755
	PF I.2 (2 Inputs)	0.0466	0.0378	0.0809	0.0749
	PF I.3 (3 Inputs)	0.0597	0.0517	0.0877	0.0796
	PF I.4 (4 Inputs)	0.1161	0.1053	0.1219	0.1140

Performance criterion: Mean absolute deviation (MAD). DGP: DMU = 50, 100; *Error term*: Noise-to-signal ratio (NTS): 0 and 1; $u_j \sim \text{Exp}(\mu = 1/6)$; Heteroscedasticity: NO; *Production function*: PF I (Cobb Douglas with increasing returns to scale); Collinearity: 0; Input distribution: $z_j \sim U(5,15)$; Number of inputs(z): m = 1, 2, 3 and 4

Monte Carlo Simulations – Example 3

Example: Omitted variables

Table 15 Omitted Variables

Method	NTS	0		1		*0*		*1*	
	DMU	50	100	50	100	*50*	*100*	*50*	*100*
DEA	PF I.4 Cobb-Douglas (IRS)	0.0644	0.0648	0.1290	0.1578	*0.0704*	*0.0588*	*0.1065*	*0.1231*
	PF I.C.4 Cobb-Douglas (DRS)	0.0537	0.0486	0.1325	0.1504	*0.0714*	*0.0531*	*0.1091*	*0.1220*
	PF II.4 CRESH	0.0662	0.0598	0.1279	0.1622	*0.0739*	*0.0613*	*0.1018*	*0.1205*
	PF III.4 Translog	0.0798	0.0796	0.1444	0.1731	*0.0668*	*0.0525*	*0.1112*	*0.1355*
SFA MoM	PF I.4 Cobb-Douglas (IRS)	0.0857	0.0865	0.0983	0.1033	*0.0606*	*0.0598*	*0.0962*	*0.1035*
	PF I.C.4 Cobb-Douglas (DRS)	0.0767	0.0766	0.0977	0.0966	*0.0747*	*0.0722*	*0.0906*	*0.0989*
	PF II.4 CRESH	0.0811	0.0876	0.1078	0.1016	*0.0618*	*0.0745*	*0.1000*	*0.1011*
	PF III.4 Translog	0.0896	0.0878	0.1101	0.1092	*0.0663*	*0.0805*	*0.0925*	*0.0958*
SFA ML	PF I.4 Cobb-Douglas (IRS)	0.0676	0.0698	0.1062	0.1023	*0.0150*	*0.0082*	*0.1052*	*0.0958*
	PF I.C.4 Cobb-Douglas (DRS)	0.0505	0.0487	0.1072	0.0933	*0.0171*	*0.0074*	*0.1015*	*0.0980*
	PF II.4 CRESH	0.0678	0.0683	0.1189	0.0955	*0.0368*	*0.0352*	*0.1105*	*0.0955*
	PF III.4 Translog	0.0888	0.0827	0.1231	0.1057	*0.0175*	*0.0094*	*0.1023*	*0.0896*
StoNED MoM	PF I.4 Cobb-Douglas (IRS)	0.0820	0.0841	0.0984	0.1036	*0.0922*	*0.0854*	*0.1019*	*0.1046*
	PF I.C.4 Cobb-Douglas (DRS)	0.0731	0.0798	0.0959	0.0975	*0.0944*	*0.0879*	*0.0951*	*0.1011*
	PF II.4 CRESH	0.0846	0.0855	0.1088	0.1038	*0.0867*	*0.0843*	*0.0967*	*0.1015*
	PF III.4 Translog	0.0904	0.0911	0.1093	0.1131	*0.0852*	*0.0837*	*0.0973*	*0.0961*
StoNED PL	PF I.4 Cobb-Douglas (IRS)	0.0681	0.0680	0.0865	0.0823	*0.1161*	*0.1053*	*0.1219*	*0.1140*
	PF I.C.4 Cobb-Douglas (DRS)	0.0632	0.0645	0.0851	0.0829	*0.1119*	*0.0952*	*0.1134*	*0.1104*
	PF II.4 CRESH	0.0704	0.0648	0.0857	0.0798	*0.1122*	*0.0995*	*0.1125*	*0.1063*
	PF III.4 Translog	0.0723	0.0765	0.0918	0.0876	*0.1130*	*0.0979*	*0.1119*	*0.1028*

Performance criterion: Mean absolute deviation (MAD). DGP: DMU = 50, 100; *Error term*: Noise-to-signal ratio (NTS): 0 and 1; $u_j \sim$ Exp(μ = 1/6); Heteroscedasticity: NO; *Production function*: See Table 13; Collinearity: 0; Input distribution: $z_j \sim$ U(5,15); Number of inputs(z) within the DGP (efficiency estimation): m = 4 (3)