Hampf, Benjamin

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Rational Inefficiency, Adjustment Costs and Sequential Technologies

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Abstract
In this paper we propose a novel approach to estimate the rational inefficiency of decision making units in the presence of adjustment costs. Using sequential definitions of the production technology, we show how cost inefficiency can be decomposed into rational and residual inefficiency as well as inefficiency caused by technical change. Furthermore, we estimate lower bounds for the unobserved adjustment costs based on unexploited cost reductions due to rational inefficiency. These adjustment costs are used to evaluate the feasibility of exploiting cost reductions caused by residual inefficiency. We demonstrate the empirical applicability of our model by estimating and decomposing the cost inefficiency of U.S. coal-fired power plants using panel data which cover the period between 1994 and 2009.

JEL classification: D24, L20, O33
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1 Introduction

The classical approaches to evaluate the efficiency of decision making units (DMUs), e.g. firms, assume that inefficiencies arise because DMUs are unaware of and, hence, do not exploit all technological possibilities (see e.g. Fried et al. (2008) for an overview of the literature). For example, analyses of cost inefficiency quantify potentials to decrease costs by radial reductions of input consumption (technical inefficiency) and by factor substitution (allocative inefficiency) given the available production technology. This methodology implicitly assumes that all inefficiencies can be reduced without costs. Therefore, DMUs do not face any adjustment costs for shifts towards the technological frontier to reduce technical inefficiencies or along the frontier to reduce allocative inefficiencies. However, as pointed out by Wibe (2008) this assumption may lead to seriously biased results if i.e. technical efficiency can only be achieved by investing in new equipment (e.g. modern computers) and these expenditures are larger than the cost reductions due to increased efficiency. In this case, firms are misclassified as operating economically inefficient.

This situation is an example of rational inefficiency, a concept which has been introduced by Bogetoft and Hougaard (2003). They point out that inefficiency as measured by production economists may be the result of rational behavior based on an unknown utility function of the decision makers of a DMU. For example, cost inefficiencies due to excess payments to employees may be explained by the objective of the management to increase the loyalty of the employees and prevent them from switching to another firm. Asmild et al. (2013) apply this model to analyze the efficiency of bank branches in Canada and evaluate whether the found inefficiencies are rational. While this approach allows to address the plausibility of inefficiency results, it does not allow to disentangle and quantify the extend of rational and residual inefficiency associated with economic inefficiency.[1] Fandel and Lorth (2009), Färe et al. (2012) and Lee and Johnson (2015) define rational inefficiency in the context of price reactions in markets with limited competition, hence where the assumption of price taking behavior can not be maintained. For example, in an oligopoly it may be rational for a firm not to produce its technologically maximal amount of outputs since the increased supply may reduce the price and thus may lead to a decrease in the firms profits.

Both approaches to rational inefficiency are based on static models which do not account for dynamic behavior or adjustment costs. Dynamic models of inefficiency (see e.g. Sengupta (1999), Nemoto and Goto (1999, 2003), Silva and Stefanou (2003, 2007) and Atkinson and Cornwell (2011)) estimate optimal paths of dynamic efficiency accounting for adjustment costs.[2] In these models DMUs can be rationally inefficient if the adjustment costs associated with reaching the technological frontier are higher than the intertemporal cost reductions.[3] However, in order to combine efficiency analysis and dynamic optimization these models are based on rather restrictive assumptions regarding the information of the analyzed DMUs, the uniqueness of the classification of inputs and the possibilities to estimate key variables (see e.g. Fallah-Fini et al. (2014)

[1] We refer to residual inefficiency as the part of economic inefficiency which can not be explained by rational behavior of the DMU.

[2] See Førsund (2010) for an overview of the literature on dynamic efficiency models.

[3] Note that the term rational inefficiency is not used in the literature on dynamic inefficiency. There it is common to address this issue by differentiating static from dynamic inefficiency. However, firm behavior which leads to static inefficiencies but is dynamic efficient can be seen as a special case of rational inefficient behavior.

for an overview of the models and the assumptions). For example, all DMUs are assumed to exhibit perfect anticipation of future variables (e.g. prices). Moreover, inputs can be clearly differentiated into variable and quasi-fixed factors with the latter being associated with adjustment costs. Both assumptions are rather questionable from an empirical point-of-view. In particular, the conventional approach to assume that capital is the single quasi-fixed input while all other factors are variable is challenged by empirical findings. While there is a long debate whether labor is a variable factor (see e.g. Hall (2004)), recent studies for power plants (see Carlson et al. (2000) and Abadie and Chamorro (2009)) found that materials (specifically: fuels) may not be variable either and, thus, without adjustment costs due to long-term contracts and costs associated with switching fuel types. This also leads to difficulties when estimating the adjustment costs as done in the above summarized models since the adjustment costs of multiple factors may be interrelated and direct data on adjustment costs as used by de Mateo et al. (2006) may not be available.

In this paper we propose a new approach to estimate the rational inefficiency of DMUs taking into account adjustment costs and a dynamic production structure. We extend the concept of Bogetoft and Hougaard (2003) to an analysis of cost inefficiencies and present a possibility to decompose the overall economic inefficiency into rational and residual inefficiency. In contrast to previous dynamic models of inefficiency, we do not rely on dynamic optimization to quantify inefficiency and impose only minimal assumptions regarding the information of the firms and the structure of the production technology. Our model is based on the assumption that at each point in time t the DMUs have knowledge about their individual production structure in t and all previous periods. That is, DMUs do not "forget" once exploited production possibilities. On an aggregate level for all DMUs this assumption leads to sequential technologies (see Tulkens and Vanden Eeckaut (1995)) where the technology set in period t contains the production points of period t and all previous periods. The difference between individual and overall sequential production possibilities allows to estimate the inefficiency with regard to a known production structure due to adjustment costs (rational inefficiency) as well as with regard to potentially unknown production points (residual inefficiency). These components can be further decomposed into technical and allocative inefficiency as well as inefficiency caused by technical change. Based on the unexploited cost reductions due to rational inefficiency, lower bounds on the adjustment costs can be estimated and used to evaluate the feasibility of exploiting the residual inefficiency.

We apply our model to an analysis of the cost efficiency of coal-fired power plants in the United States. Based on a sample covering the years 1994 to 2009 we find that conventional models of cost efficiency indicate potential cost reductions of 35% on average. However, using our decomposition we find that 10% of these potential reductions can be explained by rational inefficiency. Moreover, only half of the remaining residual inefficiency can be exploited if adjustment costs are taken into account.

This paper is structured as follows: Section 2 presents the methodology of our new approach to rational inefficiency while section 3 presents the data and results of our analysis of U.S. power plants. Finally, section 4 concludes the paper.

2 Methodology

In this section we present the theory of our approach to rational inefficiency. We start by discussing relevant theoretical concepts from production economics as well as the nonparametric estimation of sequential technologies. This is followed by a presentation of our new model to estimate rational and residual inefficiency. Finally, the consequences of different assumptions regarding the structure of adjustment costs for the feasibility of exploiting the residual inefficiency are discussed.

2.1 Modeling and estimating sequential technologies

In the following we consider a production process where m inputs $\boldsymbol{x} \in \mathbb{R}_+^m$ are used to produce k outputs $\boldsymbol{y} \in \mathbb{R}_+^k$. The technology set of this process, which comprises all technically feasible input-output combinations, is defined as:

$$T = \left\{ (\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{m+k} : \boldsymbol{x} \text{ can produce } \boldsymbol{y} \right\}. \tag{2.1}$$

Since our subsequent discussion of cost inefficiency and its decomposition into rational and residual inefficiency relies on input orientation we present the relevant axioms from production theory using the input correspondence of T, $L : \mathbb{R}_+^k \rightarrow 2^{\mathbb{R}_+^m}$, which maps outputs into subsets of inputs. The images of this correspondence are the input requirement sets (or input sets) for T and are defined as:

$$L(\boldsymbol{y}) = \left\{ \boldsymbol{x} \in \mathbb{R}_+^m : (\boldsymbol{x}, \boldsymbol{y}) \in T \right\}. \tag{2.2}$$

Following Shephard (1970) we assume that these input sets satisfy the following axioms (see Färe and Primont (1995) for further discussions on these axioms):

1. Inactivity: $\boldsymbol{x} \in L(\boldsymbol{0})$.
2. No free-lunch: $\boldsymbol{0} \notin L(\boldsymbol{y})$ if $\boldsymbol{y} \geq \boldsymbol{0}$.[4]
3. Strong disposability of inputs: If $\boldsymbol{x} \in L(\boldsymbol{y})$ and $\boldsymbol{x}' \geqq \boldsymbol{x}$, then $\boldsymbol{x}' \in L(\boldsymbol{y})$.
4. Strong disposability of outputs: If $\boldsymbol{x} \in L(\boldsymbol{y})$ and $\boldsymbol{y}' \leqq \boldsymbol{y}$, then $\boldsymbol{x} \in L(\boldsymbol{y}')$.
5. Convexity: If $\boldsymbol{x}_1 \in L(\boldsymbol{y})$ and $\boldsymbol{x}_2 \in L(\boldsymbol{y})$, then $\alpha\boldsymbol{x}_1 + (1-\alpha)\boldsymbol{x}_2 \in L(\boldsymbol{y})$ with $\alpha \in [0, 1]$.
6. Closeness: $L(\boldsymbol{y})$ is a closed set.

The inactivity axiom implies that "doing nothing" is technically feasible while the no free-lunch axiom ensures that outputs can not be produced without using any inputs. Strong disposability of inputs and outputs allows for inefficiency, e.g. given an input-output combination the same amount of outputs can be produced using more inputs and the same amount of inputs can be used to produce less outputs.[5] Convexity implies that convex combinations of feasible input vectors are also part of the input set while the closeness axiom ensures that the closure of the input set is also part of the set.

[4] Here and in the following $\geq$ and $\leq$ imply that at least one element of the vector has to satisfy inequality, while $\geqq$ and $\leqq$ imply that all elements can hold with equality.

[5] Our model can also be applied if inputs and/or outputs are only weakly disposable (see e.g. Färe et al. (1989)).

The closure (or isoquant) of the input set $L(\boldsymbol{y})$ can be defined as (see Färe et al. (1993)):

$$Isoq(\boldsymbol{y}) = \left\{\boldsymbol{x} \in \mathbb{R}^m_+ : \gamma\boldsymbol{x} \notin L(\boldsymbol{y}), 0 \leqq \gamma < 1\right\}. \tag{2.3}$$

Hence, the isoquant for an output vector $\boldsymbol{y}$ comprises all input vectors for which no proportional (radial) reduction is feasible given that the scaled input vector should be capable of producing $\boldsymbol{y}$.

The above discussed technology is based on a static setting. In our model we assume that panel data for $i = 1, \ldots, n$ DMUs covering $t = 1, \ldots, T$ periods are available. The equivalent of the static technology set in a dynamic setting is the contemporaneous technology set:

$$T^t = \left\{(\boldsymbol{x}_t, \boldsymbol{y}_t) \in \mathbb{R}^{m+k}_+ : \boldsymbol{x}_t \text{ can produce } \boldsymbol{y}_t\right\}. \tag{2.4}$$

The term "contemporaneous" indicates that this set is only based on observations from period t (see Tulkens and Vanden Eeckaut (1995) for the definitions and further discussions of panel data technologies). The corresponding input sets are defined as:

$$L^t(\boldsymbol{y}_t) = \left\{\boldsymbol{x}_t \in \mathbb{R}^m_+ : (\boldsymbol{x}_t, \boldsymbol{y}_t) \in T^t\right\}. \tag{2.5}$$

In contrast to the contemporaneous technology set, the sequential technology set for period t contains all input-output combinations which are attainable in period t as well as all combinations which were technically feasible in previous periods. Formally, the sequential input sets are defined as:

$$\widetilde{L}^t(\boldsymbol{y}_t) = \text{convex}\left\{\bigcup_{s=1}^{t} L^s(\boldsymbol{y}_t)\right\}. \tag{2.6}$$

Hence, the sequential input sets of period t are given by the convex hull of the union of all contemporaneous input sets of time periods 1 to t. The convex hull implies that convex combinations between observations of different periods are also technically feasible. Therefore, contemporaneous as well as sequential input sets satisfy the convexity axiom.[6] We further assume that the dynamic input sets satisfy all remaining axioms stated above.

Based on the input sets of two different time periods, shifts in the frontiers can be used to calculate technical changes.[7] Shestalova (2003) proposes a model to estimate technical change based on sequential technologies.[8] In our following discussion we will show how a specific assumption regarding the structure of the technical change can be used to simplify the estimation of the inefficiency caused by technical change in our model.

7. Implicit Hicks input neutrality: $L^t(\boldsymbol{y}_t) = \frac{\bar{L}(\boldsymbol{y}_t)}{A(t,\boldsymbol{y}_t)}$

The axiom of implicit Hicks input neutrality has been proposed for single output technologies by Blackorby et al. (1976) and for the case of multiple outputs by Chambers and Färe (1994) (see Färe and Grosskopf (1996) for a detailed discussion of the axiom). Here, $A(t, \boldsymbol{y}_t)$ denotes

[6] See O'Donnell et al. (2008) for a discussion of the analysis of convex and non-convex unions of technology sets.
[7] See Agrell and West (2001) for a comparison of different indices to measure productivity and technical change and their relationship to the optimizing behavior of the firms.
[8] Note that the use of sequential technologies precludes the possibility of technological regress. However, as pointed out by Shestalova (2003) technical regress is rarely observed in production processes of industrialized countries.

the factor of technical change which proportionally scales the time independent (basic) input set $\bar{L}(\boldsymbol{y}_t)$. Implicit Hicks input neutrality implies that the input sets are shifted radially, hence the technical change is ray-preserving.

Combining implicit Hicks input neutrality and a sequential definition of the input sets we find that the input sets satisfy

$$
\begin{aligned}
\widetilde{L}^t(\boldsymbol{y}_t) &= \text{convex}\left\{\bigcup_{s=1}^{t} L^s(\boldsymbol{y}_t)\right\} \\
&= \text{convex}\left\{\bigcup_{s=1}^{t} \frac{\bar{L}(\boldsymbol{y}_t)}{A(s,\boldsymbol{y}_t)}\right\} \\
&= \text{convex}\left\{\frac{\bar{L}(\boldsymbol{y}_t)}{\max\limits_{s\in\{1,\dots,t\}} A(s,\boldsymbol{y}_t)}\right\} \\
&= \frac{\bar{L}(\boldsymbol{y}_t)}{\max\limits_{s\in\{1,\dots,t\}} A(s,\boldsymbol{y}_t)}.
\end{aligned}
\tag{2.7}
$$

In this derivation the first equality follows from the definition of the sequential input sets while the second follows from implicit Hicks input neutrality. The third equality follows from the possibility to dispose inputs while the last equality follows from the convexity of the input sets. This derivation shows that given implicit Hicks input neutral technical change the sequential input set of period t can be calculated as the maximal radial expansion between periods 1 and t of the basic input set caused by technical change.

In order to estimate the sequential input sets we rely on nonparametric methods (Data Envelopment Analysis, DEA) by Charnes et al. (1978) which in contrast to parametric methods do not impose a specific functional form on the isoquants of the input sets. Given a sample of $i = 1, \dots, n$ observations with input-output combinations $(\boldsymbol{x}_{t,i}, \boldsymbol{y}_{t,i})$ covering $t = 1, \dots, T$ periods the DEA estimation of the sequential input sets reads as:

$$
\widehat{\widetilde{L}^t}(\boldsymbol{y}_t) = \left\{\boldsymbol{x} : \boldsymbol{x} \geqq \widetilde{\boldsymbol{X}}_t\boldsymbol{\lambda}_t, \boldsymbol{y}_t \leqq \widetilde{\boldsymbol{Y}}_t\boldsymbol{\lambda}_t, \boldsymbol{\lambda}_t \geqq \mathbf{0}, \mathbf{1}^T\boldsymbol{\lambda}_t = 1\right\}. \tag{2.8}
$$

In this formulation, $\widetilde{\boldsymbol{X}}_t$ denotes the $m \times (n \cdot t)$ matrix of inputs and $\widetilde{\boldsymbol{Y}}_t$ the $k \times (n \cdot t)$ matrix of outputs from periods $s = 1, \dots, t$. $\boldsymbol{\lambda}_t$ denotes the $(n \cdot t) \times 1$ vector of weight factors which are used to obtain the convex combinations of observations that span the frontier. Following Banker et al. (1984) the weight factors are restricted to be non-negative and to sum up to unity implying that the technology exhibits variable returns to scale (VRS).[9] The estimation of the set can be modified to exhibit constant returns to scale (CRS) by dropping the summing-up restriction.

2.2 Measuring and decomposing rational inefficiency

In the following we discuss how economic inefficiency can be decomposed into rational and residual inefficiency based on the assumption of sequential technologies. In our discussion we focus on the

[9] The non-convex version of the model, the Free Disposal Hull estimator by Deprins et al. (1984), can be obtained by adding the restriction $\boldsymbol{\lambda}_t \in \{0, 1\}$.

decomposition of cost inefficiency. However, the same structure of decomposition can be applied to analyses of revenue or profit inefficiency.

Our approach to estimate the rational inefficiency of DMUs is based on comparing the inefficiency results obtained from analyzing the overall sequential input sets $\widetilde{L}^t(\boldsymbol{y}_t)$ defined above and the DMU-specific individual sequential input sets $\widetilde{L}_i^t(\boldsymbol{y}_t)$. We define the individual input sets as:

$$\widetilde{L}_i^t(\boldsymbol{y}_t) = \text{convex}\left\{\boldsymbol{x} \geqq \boldsymbol{x}_{s,i} \in \mathbb{R}_+^m : \boldsymbol{x}_{s,i} \text{ can produce } \boldsymbol{y}_t, s \in \{1, \ldots, t\}\right\}. \tag{2.9}$$

The individual isoquants (or frontiers) corresponding to $\widetilde{L}_i^t(\boldsymbol{y}_t)$ are denoted by $\widetilde{Isoq}_i^t(\boldsymbol{y}_t)$. Analogously to the overall sequential input sets, $\widetilde{L}_i^t(\boldsymbol{y}_t)$ contains the current and all past input combinations of DMU i which can produce the output vector $\boldsymbol{y}_t$ implying that the DMU does not "forget" once exploited production possibilities. Moreover, we assume that the axioms defined above can also be imposed on $\widetilde{L}_i^t(\boldsymbol{y}_t)$ implying that the DMUs do not only have knowledge about their current and past production points but are also aware of the possibilities to produce inefficiently (due to the free disposability of inputs) and to combine the input vectors (due to the convexity of the set). By definition $\widetilde{L}_i^t(\boldsymbol{y}_t) \subseteq \widetilde{L}^t(\boldsymbol{y}_t)$ implying that the cost inefficiency based on $\widetilde{L}_i^t(\boldsymbol{y}_t)$ can never be larger than the cost inefficiency based on $\widetilde{L}^t(\boldsymbol{y}_t)$. Moreover, since we assume $\boldsymbol{y}_t = \boldsymbol{y}_{t,i}$ when analyzing the inefficiency of the DMUs it follows that $\widetilde{L}_i^t(\boldsymbol{y}_t) \neq \emptyset$ and the proposed decomposition is always feasible. The nonparametric estimator $\widehat{\widetilde{L}_i^t}(\boldsymbol{y}_t)$ can be obtained by replacing the matrices $\widetilde{\boldsymbol{X}}_t$ and $\widetilde{\boldsymbol{Y}}_t$ in equation (2.8) by the matrices $\widetilde{\boldsymbol{X}}_{t,i}$ and $\widetilde{\boldsymbol{Y}}_{t,i}$ which only contain the input and output vectors of DMU i for $s = 1, \ldots, t$.

In line with the literature on cost inefficiency we assume that the DMUs are cost minimizers. Hence, given their available information on prices and technological possibilities they minimize the costs of producing $\boldsymbol{y}_t$. However, in contrast to the conventional approaches we assume that changes in the input vectors are associated with adjustment costs. The adjustment costs can be associated with radial movements to the frontier (e.g. cost associated with optimizing production chains which allows to reduce the number of low and high skilled workers) or non-radial movements along the frontier (e.g. firing and hiring costs in order to replace high skilled by low skilled workers). We assume that while these costs are unobservable for the researcher, they are known to the DMUs. Therefore, they affect the cost minimization of the DMUs. Differentiating the individual and the overall sequential input sets allows to analyze inefficiency with regard to the known production possibilities contained in $\widetilde{L}_i^t(\boldsymbol{y}_t)$ and with regard to potentially unknown production possibilities contained in $\widetilde{L}^t(\boldsymbol{y}_t)$. Given the assumption of cost minimizing behavior and unobserved adjustment costs, the inefficiency based on $\widetilde{L}_i^t(\boldsymbol{y}_t)$ can be classified as rational inefficiency since the optimizing DMU chooses an inefficient input combination although it is aware of *seemingly* superior, less cost intensive input combinations as contained in the individual inputs set. We interpret this inefficiency as being caused by the unobserved adjustment costs.

This approach to rational inefficiency and adjustment costs can also be interpreted in the sense of Bogetoft and Hougaard (2003). For example, if the adjustment costs in form of reduced motivation of employees are higher than the decrease in labor costs due to the reduction of bonus payments, then the DMU operates rationally inefficient by choosing a point which lies within $\widetilde{L}_i^t(\boldsymbol{y}_t)$.[10]

[10] In this example we assume that the labor costs are an input of the production process.

However, in contrast to Bogetoft and Hougaard (2003) our model does not necessarily attribute all inefficiency to either entirely rational or non-rational behavior.

In our approach the residual (possibly non-rational) inefficiency is measured as the difference between the inefficiency as measured by exploiting the overall sequential input sets and the estimated rational inefficiency. This inefficiency may result because the DMUs are not aware of the additional technological possibilities captured in the overall set $\widetilde{L}^t(\boldsymbol{y}_t)$. Hence, this inefficiency is potentially non-rational and should be decreased by the DMUs. However, following the argument by Wibe (2008) the additional production possibilities may be caused by technical progress which can only be exploited by investing in new technologies. Without any further information regarding the costs associated with following the technical progress, this type of inefficiency can not be classified as being non-rational. Therefore, we further differentiate inefficiency caused by technical change from residual inefficiency.

To formally define our decomposition of cost inefficiency into rational and residual inefficiency as well as technical change, we consider the cost functions based on the overall and the individual sequential input sets:

$$C^t(\boldsymbol{p}_t, \boldsymbol{y}_t) = \min_{\boldsymbol{x}} \left\{ \boldsymbol{p}_t^T \boldsymbol{x} : \boldsymbol{x} \in \widetilde{L}^t(\boldsymbol{y}_t) \right\}, \boldsymbol{p}_t > \boldsymbol{0}, \tag{2.10}$$

$$C_i^t(\boldsymbol{p}_t, \boldsymbol{y}_t) = \min_{\boldsymbol{x}} \left\{ \boldsymbol{p}_t^T \boldsymbol{x} : \boldsymbol{x} \in \widetilde{L}_i^t(\boldsymbol{y}_t) \right\}, \boldsymbol{p}_t > \boldsymbol{0}. \tag{2.11}$$

Here, $\boldsymbol{p}_t$ denotes the $m \times 1$ vector of input prices of period t which we assume to be strictly positive.[11] In order to reduce the notational complexity we assume that the input prices are the same for all DMUs. If the prices differ, then $\boldsymbol{p}_t$ can be replaced by $\boldsymbol{p}_{t,i}$ in the cost functions and our following decompositions. Estimates of the cost functions as well as the following distance functions can be obtained by replacing the unknown sequential input sets by the nonparametric estimators from equation (2.8). The resulting cost minimizing input vectors of the overall and the individual cost function are denoted by $\boldsymbol{x}^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)$ and $\boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)$. It is important to note that due to the use of sequential input sets the individual frontier and, hence the cost minimizing input vector, may not consist of observations from period t. We denote by $r \leqq t$ the period based on which the frontier is constructed. If the frontier is constructed using observations from different periods, then r is equal to the most recent period included in the convex combinations since the input set of this period also includes all previous input combinations. Particularly relevant for our analysis is the case that $\widetilde{L}_i^r(\boldsymbol{y}_t) = \widetilde{L}_i^t(\boldsymbol{y}_t)$ but $\widetilde{L}^r(\boldsymbol{y}_t) \subset \widetilde{L}^t(\boldsymbol{y}_t)$ implying that technical progress has occurred for the overall technology between periods r and t, but DMU i did not follow this technical change. In this case inefficiency due to unexploited technical progress arises.

Based on the cost functions we measure and decompose the cost efficiency of a DMU i as:

$$CE_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t) = \frac{C^t(\boldsymbol{p}_t, \boldsymbol{y}_t)}{\boldsymbol{p}_t^T \boldsymbol{x}_t} = \underbrace{\frac{C_i^t(\boldsymbol{p}_t, \boldsymbol{y}_t)}{\boldsymbol{p}_t^T \boldsymbol{x}_t}}_{RAT_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t)} \times \underbrace{\frac{C^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}{C_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}}_{RES_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t)} \times \underbrace{\frac{C^t(\boldsymbol{p}_t, \boldsymbol{y}_t)}{C^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}}_{TC_i^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t)}. \tag{2.12}$$

Here, $CE_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t)$ denotes the cost efficiency of DMU i, while $RAT_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t)$ denotes the

[11] The assumption $\boldsymbol{p}_t > \boldsymbol{0}$ ensures that the infinum of the cost function is a minimum.

rational efficiency. The residual efficiency is represented by $RES_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t)$ and $TC_i^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t)$ measures the efficiency with regard to technical change.[12] Values less than unity imply inefficiency with regard to the analyzed component. Hence, the percentage amount of cost inefficiency and possible cost reductions can be calculated as $100 \times \left(1 - CE_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t)\right)$. The inefficiency and the associated cost reductions for the components can be estimated likewise.

As discussed above, the rational inefficiency is measured as the cost inefficiency relative to the individual sequential input set of DMU i. Note that by definition $C_i^t(\boldsymbol{p}_t, \boldsymbol{y}_t) = C_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t)$ and $\boldsymbol{x}_i^{r,*}(\boldsymbol{p}_t, \boldsymbol{y}_t) = \boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)$. Therefore, the residual inefficiency measures the difference in the minimal costs with regard to the overall and the individual input set for period r. This approach allows to disentangle residual inefficiency from inefficiency caused by technical progress. The additional inefficiency is measured by the third component in the above decomposition. This component is based on the technical change that occurred for the overall frontier between periods r and t. Hence, it measures the extent of technical progress which has not been exploited by DMU i. It exhibits a value equal to unity if either no technical change has occured or $r = t$ implying that DMU i has shifted its individual frontier and therefore followed technical change. By differentiating shifts in the overall technology from shifts in the individual frontier our model accounts for localized technical progress as introduced by Atkinson and Stiglitz (1969). For example, learning-by-doing may enhance the production possibilities for the overall frontier while this is not possible given the individual technology.

Applying the Farrell (1957) measure of technical input efficiency allows to further decompose the efficiency components into radial (technical) and non-radial (allocative) efficiency. While the technical efficiency measures equiproportional decreases in all inputs, the allocative efficiency measures cost reduction potentials due to changes in the input mix, hence due to movements along the isoquant. The radial Farrell measures corresponding to the cost functions are defined as:

$$\theta^t(\boldsymbol{x}_t, \boldsymbol{y}_t) = \min\left\{\theta : \theta\boldsymbol{x}_t \in \widetilde{L}^t(\boldsymbol{y}_t)\right\}, \tag{2.13}$$

$$\theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t) = \min\left\{\theta : \theta\boldsymbol{x}_t \in \widetilde{L}_i^t(\boldsymbol{y}_t)\right\}. \tag{2.14}$$

Based on these measures the decomposition of the components reads as:

$$RAT_i^t(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{y}_t) = \underbrace{\theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)}_{TE_{RAT,i}^t(\boldsymbol{x}_t, \boldsymbol{y}_t)} \times \underbrace{\frac{C_i^t(\boldsymbol{p}_t, \boldsymbol{y}_t)}{\boldsymbol{p}_t^T \theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\,\boldsymbol{x}_t}}_{AE_{RAT,i}^t(\boldsymbol{x}_t, \boldsymbol{p}_t, \boldsymbol{y}_t)}, \tag{2.15}$$

$$RES_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t) = \underbrace{\theta^r\left(\boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t), \boldsymbol{y}_t\right)}_{TE_{RES,i}^r(\boldsymbol{p}_t, \boldsymbol{y}_t)} \times \underbrace{\frac{C^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}{\theta^r\left(\boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t), \boldsymbol{y}_t\right) C_i^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}}_{AE_{RES}^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}, \tag{2.16}$$

$$TC_i^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t) = \underbrace{\theta^t\left(\boldsymbol{x}^{r,*}(\boldsymbol{p}_t, \boldsymbol{y}_t), \boldsymbol{y}_t\right)}_{TE_{TC,i}^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t)} \times \underbrace{\frac{C^t(\boldsymbol{p}_t, \boldsymbol{y}_t)}{\theta^t\left(\boldsymbol{x}^{r,*}(\boldsymbol{p}_t, \boldsymbol{y}_t), \boldsymbol{y}_t\right) C^r(\boldsymbol{p}_t, \boldsymbol{y}_t)}}_{AE_{TC,i}^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t)}. \tag{2.17}$$

[12] Due to the use of sequential input sets all technical change is technical progress.

In this decomposition, $TE_{TC,i}^{r,t}(\boldsymbol{p}_t, \boldsymbol{y}_t)$ measures the additional radial reductions in the input vector due to technical progress relatively to the cost-minimizing point on the overall frontier of period r. If the technical change is implicit Hicks input neutral (see axiom 7 in the previous section), then the result for this component is independent of the point from which the shift in the frontier is measured. Hence, $\boldsymbol{x}^{r,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)$ does not need to be estimated in order to estimate the radial influence of technical change and the measure is independent of the prices of the inputs which define the cost-minimizing point on the frontier. Combining this finding with result (2.7) it follows that

$$TE_{TC,i}^{r,t}(\boldsymbol{y}_t) = \max_{s\in\{1,\ldots,r\}} A(s, \boldsymbol{y}_t) \times \left[\max_{s\in\{1,\ldots,t\}} A(s, \boldsymbol{y}_t)\right]^{-1} \tag{2.18}$$

implying that in case of Hicks input neutrality the measure can be interpreted as the ratio of maximal expansions of the overall input sets.

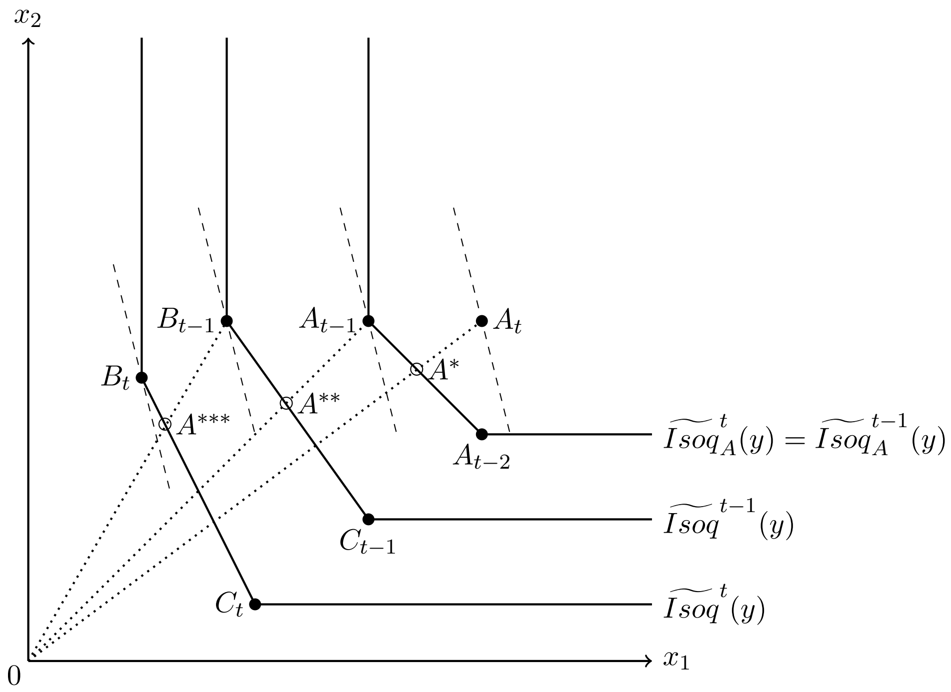

Figure 1: Example of rational and residual inefficiency

To visualize our approach to rational inefficiency, figure 1 depicts the overall and individual sequential input sets based on three different DMUs (A, B and C). The DMUs are using two inputs x_1 and x_2 to produce a single output y. The amount of produced output is equal for all DMUs and fixed for all time periods in order to depict the decomposition in input space. The dashed lines in the figure represent isocost lines. The bold lines $\widetilde{Isoq}^{\,t}(y)$ and $\widetilde{Isoq}^{\,t-1}(y)$ represent the isoquants for the overall sequential input sets, while $\widetilde{Isoq}_A^{\,t}(y)$ represents the isoquant of the individual sequential input set for DMU A. In order to reduce the complexity of the figure, the overall sequential isoquant for period t $(t-1)$ is completely based on observations from period t $(t-1)$. This implies that the overall sequential input sets are equal to the overall contemporaneous input sets. In contrast, the individual isoquant for DMU A is based on observations from periods $t-1$ and $t-2$. Therefore, $\widetilde{Isoq}_A^{\,t}(y) = \widetilde{Isoq}_A^{\,t-1}(y)$.

Given this production structure it is obvious that in period t DMU A produces cost inefficient.

The overall cost efficient input combination to produce y in period t is given by the point B_t. The overall cost efficiency of DMU A is given by the ratio of the costs based on input bundle B_t to the actual costs associated with the point A_t. The rational efficient point is given by A_{t-1}, which can be obtained by moving to the rational technical efficient point (A^*) and changing the input structure according to the rational allocative efficient point (A_{t-1}). In this example, $r = t-1$ implying that while the overall frontier has shifted due to technical progress, no technical change regarding the individual input set can be observed. Therefore, the residual efficient point which is located on the frontier of the overall sequential input set for $r = t-1$ is B_{t-1}. The residual technical efficient point is A^{**} while B_{t-1} is allocative efficient. Due to technical progress between periods $t-1$ and t the overall frontier function shifts towards the origin. The radial input reductions could be exploited by moving from B_{t-1} to A^{***}, while the non-radial changes could be exploited by moving from A^{***} to B_t.

2.3 Adjustment costs and residual inefficiency

In the following we discuss how adjustment costs and their effect on the cost inefficiency of DMUs can be estimated based on the theoretical framework described above. We start by discussing general definitions and assumptions regarding the adjustment costs in our model. This is followed by a description of the estimation of lower bounds for the adjustment costs based on individual sequential input sets. The section concludes with a discussion of the assessment of the feasibility to exploit the residual inefficiency based on the estimated adjustment costs.

As discussed in the introduction, the empirical literature challenges the theoretical assumption that inputs can be clearly classified as quasi-fixed and variable factors, with the latter not being associated with adjustment cost. Moreover, the literature finds that adjustment costs are interrelated, hence individual adjustment costs may not be identifiable. Therefore, in our model we assume that each of the m inputs can lead to adjustment costs if the amount of the input is changed. Moreover, we analyze the aggregate costs of simultaneous adjustment of these m inputs. We denote by $AC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2)$ the (unobserved) overall adjustment costs of DMU i in period t associated with shifting from the input vector $\boldsymbol{x}_1$ to the input vector $\boldsymbol{x}_2$. Based on these costs we define the average adjustment costs (adjustment costs relative to distance) as

$$AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) = \frac{AC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2)}{||\boldsymbol{x}_1 - \boldsymbol{x}_2||} \tag{2.19}$$

where $||\boldsymbol{x}_1 - \boldsymbol{x}_2||$ denotes the Euclidean distance between $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$. We do not use the Farrell (1957) measure to estimate the distance in (2.19) since it can only be applied to measure radial distances. While, in principle, the non-radial (allocative) distances can also be measured radially as the distance of the technically efficient point to the isocost line, this distance does not only depend on the physical amount of inputs but also on the input prices. Since the distance measure should be independent of the prices we apply the Euclidean distance.[13] However, the Euclidean distance is nonetheless related to the radial measurement of inefficiency since the Farrell (1957) measure can be interpreted as the ratio of two norms (see Cooper et al. (2007)).

[13] See Briec (1998) for an approach to efficiency analyses based on Hölder norms which encompass the Euclidean distance as a special case.

In order to make our model as generally applicable as possible we only impose the minimal assumptions regarding the adjustment costs needed to conduct our analysis. In particular, we do not impose a specific functional form of the adjustment costs. Hence, the estimation of the input sets as well as the adjustment costs is nonparametric.

In our model we assume that the adjustment costs are comparable across the DMUs implying that:

$$AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) = AvAC_l^t(\boldsymbol{x}_1, \boldsymbol{x}_2) \;\; \forall i, l. \tag{2.20}$$

This assumption is needed to empirically analyze the structure of the adjustment costs as will be discussed below. Note that we do not assume that the adjustment costs are time independent. Hence, we allow for e.g. adjustment cost reducing technical progress. Furthermore, we assume that the adjustment costs are symmetric:

$$AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) = AvAC_i^t(\boldsymbol{x}_2, \boldsymbol{x}_1). \tag{2.21}$$

This assumption is particularly important for evaluating the feasibility of exploiting the residual allocative inefficiency. It ensures that the adjustment costs for movements along the frontier are not influenced by the direction of the movement.

In our model we do not impose a-priori restrictions on the structure of the adjustment costs. Although the majority of the theoretical and empirical literature assumes convex adjustment costs (see Hamermesh and Pfann (1996) for an overview of the literature), we also consider the possibility of linear (see e.g. Rothschild (1971)) or concave (see e.g. Abowd and Kramarz (2003)) adjustment costs. Therefore, the adjustment costs may exhibit:[14]

$$\begin{array}{ll} \text{Convexity:} & AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) > AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_3) \;\; \text{with } ||\boldsymbol{x}_1 - \boldsymbol{x}_2|| > ||\boldsymbol{x}_1 - \boldsymbol{x}_3|| \\ \text{Linearity:} & AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) = AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_3) \;\; \forall \boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3 \\ \text{Concavity:} & AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_2) < AvAC_i^t(\boldsymbol{x}_1, \boldsymbol{x}_3) \;\; \text{with } ||\boldsymbol{x}_1 - \boldsymbol{x}_2|| > ||\boldsymbol{x}_1 - \boldsymbol{x}_3|| \end{array} \tag{2.22}$$

To estimate the adjustment costs we build upon the results from the decomposition of the cost inefficiency discussed above. Our approach models rational inefficiency as the distance to the individual sequential input set due to adjustment costs. The unexploited cost reductions associated with moving from the actual input vector to the cost minimizing point on the individual frontier can therefore be interpreted as lower bounds on the unobserved adjustment costs. Moreover, based on the decomposition into technical and allocative rational inefficiency, lower bounds for the radial and the non-radial adjustment costs can be estimated. Formally, the bounds on the radial and the non-radial adjustment costs are given by:

$$RAvAC_i^t\left(\boldsymbol{x}_t, \theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t\right) \geqq \frac{\boldsymbol{p}_t^T\left(\boldsymbol{x}_t - \theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t\right)}{||\boldsymbol{x}_t - \theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t||}, \tag{2.23}$$

$$NRAvAC_i^t\left(\theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t, \boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)\right) \geqq \frac{\boldsymbol{p}_t^T\left(\theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t - \boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)\right)}{||\theta_i^t(\boldsymbol{x}_t, \boldsymbol{y}_t)\boldsymbol{x}_t - \boldsymbol{x}_i^{t,*}(\boldsymbol{p}_t, \boldsymbol{y}_t)||}. \tag{2.24}$$

Based on these bounds we are able to evaluate the feasibility of exploiting the cost reductions

[14] In this definition we assume that no fixed adjustment costs (see e.g. Cooper and Haltiwanger (2006)) are present.

due to residual inefficiency. Intuitively, we analyze whether the cost reductions associated with removing the residual inefficiency are smaller than the lower bounds on the adjustment costs. In this case, the cost reductions are not feasible and the DMUs operate efficiently by not investing into restructuring their input usage.

Since the input vectors analyzed to obtain the rational inefficiency and residual inefficiency and, hence, their distance may vary, assumptions regarding the structure of the adjustment costs as given by equation (2.22) need to be imposed. Based on assumption (2.20), the estimated adjustment costs for different DMUs can be used to empirically test whether the assumed structure is correct. Using the nonparametric approach by Abrevaya and Jiang (2005), this test can be conducted without imposing functional assumptions. For the case of a single explanatory variable (e.g. the distance between the input vectors in our model) a simplified version of the test has been proposed by Niermann (2007).

Based on the structural form of the adjustment costs, the conditions for the non-exploitability of the technical residual inefficiency are:

$$
\begin{aligned}
&\text{Convexity:} \frac{\boldsymbol{p}_t^T \left(x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)\right)}{||\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) \boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)||} < \frac{\boldsymbol{p}_t^T \left(\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t\right)}{||\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t||} \\
&\qquad \text{and } ||\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) \boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)|| \geqq ||\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t||, \\[2ex]
&\text{Linearity:} \frac{\boldsymbol{p}_t^T \left(x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)\right)}{||\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) \boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)||} < \frac{\boldsymbol{p}_t^T \left(\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t\right)}{||\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t||}, \quad (2.25) \\[2ex]
&\text{Concavity:} \frac{\boldsymbol{p}_t^T \left(x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) x_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)\right)}{||\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) \boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)||} < \frac{\boldsymbol{p}_t^T \left(\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t\right)}{||\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t||} \\
&\qquad \text{and } ||\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right) - \theta^r \left(\boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right), \boldsymbol{y}_t\right) \boldsymbol{x}_i^{t,*}\left(\boldsymbol{p}_t, \boldsymbol{y}_t\right)|| \leqq ||\boldsymbol{x}_t - \theta_i^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t\right) \boldsymbol{x}_t||.
\end{aligned}
$$

Similar conditions for the non-exploitability of the allocative residual inefficiency can be defined by replacing the initial amounts of inputs with the technical efficient amounts and the technical efficient amounts by the allocative efficient amounts. Note that by excluding the inefficiency effect due to technical change, we evaluate the cost reductions for the same period of the individual and the overall frontier. Hence, we do not address the cost reductions which are obtained by following technical change, e.g. by investing into new computers. Without any additional information regarding the causes and costs of technical change, we can not evaluate whether these cost reductions are feasible.

Combining the concepts of rational inefficiency, technical change and adjustment costs we are able to evaluate in detail the feasibility of reducing costs by changing the input structure of a DMU. In particular, given a situation in which the residual inefficiency can not be exploited due to high adjustment costs and the technical progress is associate with high investments, DMUs may be reclassified as operating completely economically efficient although the conventional analysis of cost inefficiencies classifies them as being inefficient.

3 Empirical application to U.S. power plants

In this section we apply our model to an analysis of the cost efficiency of coal-fired power plants in the United States. These plants haven been previously analyzed in a large number of studies on technical, economic and environmental efficiency (see e.g. Zhou et al. (2008) for a survey). Particularly relevant for our analysis are the studies on cost efficiency (see Zeitsch and Lawrence (1996), Goto and Tsutsui (1998), Olatubi and Dismukes (2000), Tone and Tsutsui (2007) and Welch and Barnum (2009)) which typically find large cost inefficiencies that are predominantly caused by allocative inefficiency.[15] Results on potential cost inefficiencies are used e.g. to evaluate whether mergers in the electric sector lead to efficiency increases (see Kwoka and Pollitt (2010)). We apply our model to evaluate whether the previously found cost inefficiencies can be explained by rational behavior. Moreover, we analyze which cost reductions are feasible if adjustment costs are taken into account. We start by describing the construction of the panel dataset. Following this description we present and discuss the results of our analysis and the decomposition of the inefficiency. The section concludes with an evaluation of the feasibility to exploit the residual inefficiency.

3.1 Construction of the dataset

In order to evaluate the efficiency of U.S. power plants we construct a dataset which is closely related to the datasets studied in the previous literature. In particular, we follow Färe et al. (2013) to obtain balanced panel data for the power plants. However, in contrast to Färe et al. (2013) we do not analyze their environmental efficiency. Therefore, we collect data for a smaller number of inputs and outputs leading to a larger sample size due to fewer missing observations.

We assume that in the production process of the plants the inputs labor, capital and fuels are used to produce the output electricity. Following Färe et al. (2007) we define plants which use coal as their primary energy source as coal-fired power plants. However, these plants may in addition also use oil and natural gas. Data on the labor input (measured in number of workers) are obtained from form 1 of the Federal Energy Regulatory Commission (FERC).[16] In this form annual information regarding the average number of employees of the plants are collected. We use the capacity of the plants (measured in megawatts, MW) which is also reported in FERC form 1 as a proxy for the capital stock. Data on the fuel inputs (measured in millions of british thermal units, BTUs) as well as the electricity output (measured in megawatt hours, MWh) are obtained from the US Energy Information Administration (EIA).[17] For the years 1994 to 2007 data are available from file EIA-767, while for the years 2006 and 2007 (2008 and 2009) these data are reported in file EIA-906 (EIA-923).

In order to evaluate the cost efficiency of the plants we also collect data on the input prices. For the price of the capital stock which is proxied by the capacity of the plants we follow Olatubi and Dismukes (2000) and use the capital costs of installed capacity (measured in $ per kilowatt, KW) as reported in FERC form 1. The fuel prices (measured in $ per BTU) are calculated as the

[15] For an analysis of regulated cost inefficiency see Granderson and Linvill (2002).
[16] The FERC data are available from `www.ferc.gov/docs-filing/forms/form-1/data.asp`.
[17] The EIA data are available from `www.eia.gov/electricity/data/detail-data.html`.

Table I: Descriptive statistics of power plant data (1994-2009)

Variable	Unit	Min.	Mean	Median	Max.	St.dev.
Inputs						
Capacity	MW	116.00	869.40	700.00	2560.05	642.92
Labor	Workers	33.00	145.33	123.00	458.00	81.28
Coal	Mill. BTUs	326693.86	51028329.85	41071286.00	190033216.00	41945363.53
Oil	Mill. BTUs	0.00	68424.21	29938.44	2794475.00	140090.17
Gas	Mill. BTUs	0.00	329711.68	0.00	30407340.00	1717936.99
Output						
Electricity	MWh	22664.00	5069017.69	4040040.00	18918042.00	4275894.99
Prices						
Capacity	$ per KW	25.47	481.69	419.98	1654.87	242.92
Labor	$ per worker	34662.98	62627.77	60924.71	95792.54	13678.82
Coal	$ per BTU	0.65	1.52	1.35	4.41	0.66
Oil	$ per BTU	0.33	7.10	5.51	25.82	4.80
Gas	$ per BTU	1.11	4.67	3.83	11.51	2.51

weighted annual average of the prices paid during the analyzed year. Data on the expenditures and purchased amounts of the fuels are obtained from file EIA-423 for the years 1994 to 2007 and from file EIA-923 for the years 2008 and 2009. Finally, the annual wages of the workers (measured in $ per worker) are collected form the County Business Patterns (CBP) of the US Census Bureau.[18] We use data on the average payment for employees in the industry sector with the North American Industry Classification Code (NAICS) "22111" (electric power production). Since several counties do not provide information regarding the annual payments we use state-level data instead of county-level data.

Our final analyzed dataset covers 37 coal-fired power plants during the period 1994 to 2009. This relatively small sample size is in line with the numbers of plants analyzed in previous studies using detailed data as described above (see e.g. Färe et al. (2013) and Hampf (2014)). Other studies which analyze larger sample sizes of power plants usually aggregate different power plant technologies (e.g. gas- and coal-fired power plants) in a single technology set (see Heshmati et al. (2012) for critical remarks on this approach) or use data on the generator-level (see e.g. Hampf and Rødseth (2015)). However, the latter approach does not capture the possibility of plants to switch between different generating units in order to decrease costs associated with producing a fixed amount of electricity. Therefore, we focus solely on plant-level data for coal-fired power plants. Descriptive statistics of the data can be found in table I.

3.2 Results of the efficiency analysis

In the following we present the results for the cost efficiency and the proposed decomposition into rational and residual efficiency for U.S. power plants. Our estimations are based on the

[18] The CBP data are available from `www.census.gov/econ/cbp/index.html`.

assumption that the production technology exhibits variable returns to scale. However, we also conducted the analysis assuming constant returns to scale and found very similar results. The differences in the average efficiency results are less than 5% and the decomposition leads to an identification of the same sources that drive cost inefficiency.

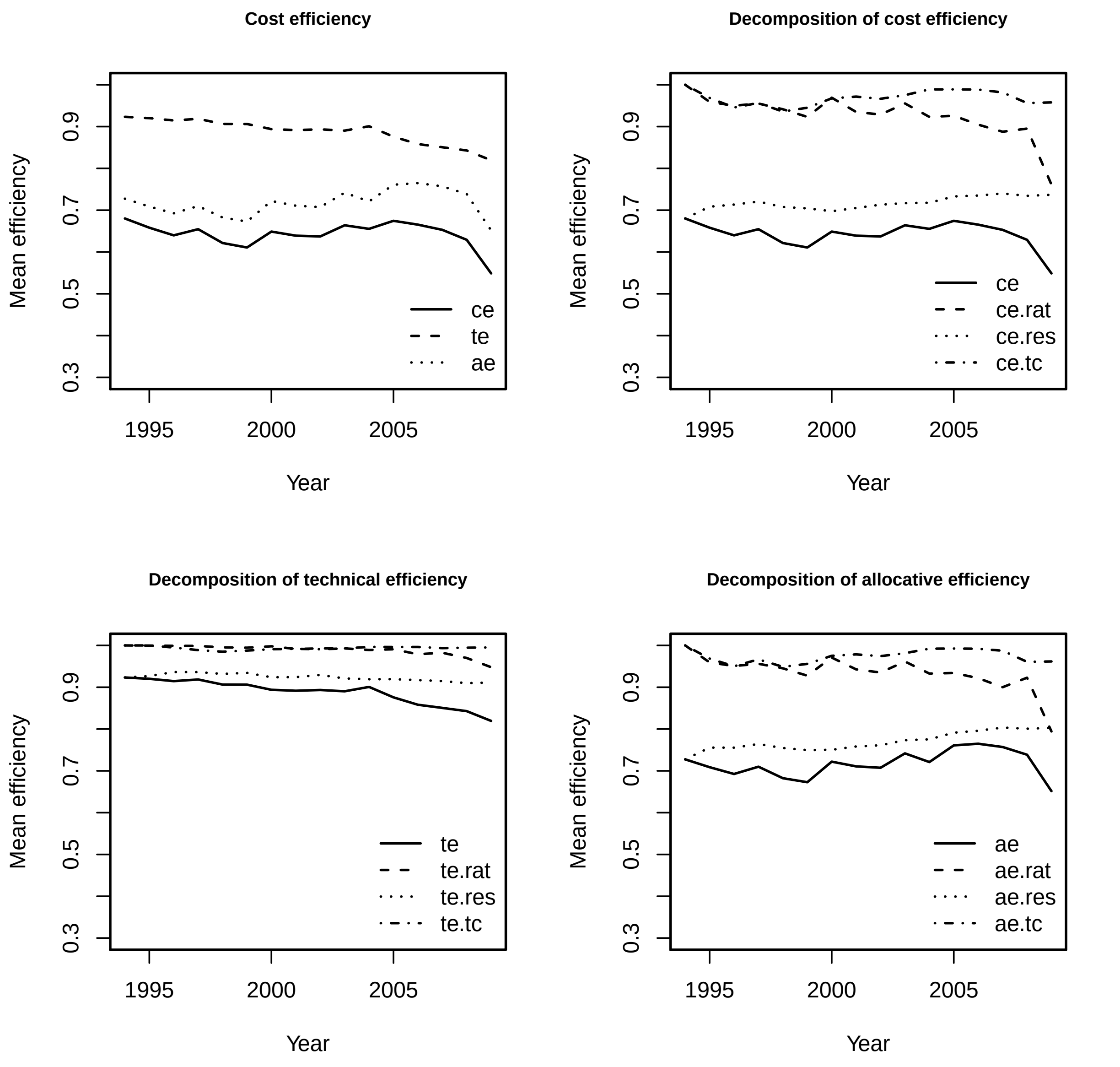

Figure 2: Results of the cost efficiency and its decomposition

Figure 2 depicts the average results of our analysis for the years 1994 to 2009. The upper left panel shows the results of a conventional analysis of cost efficiency based on overall sequential technologies.[19] The annual average results for the cost efficiency are represented by the bold line while the average technical (allocative) efficiency is represented by the dashed (dotted) line. The figure shows that the cost efficiency is about 65% and relatively stable throughout the analyzed period with the exception of the last analyzed year 2009. For this year we observe a drop in the

[19] In our presentation we focus on the average results for all plants. Detailed results for each plant and year can be obtained from the author upon request.

cost efficiency as well as the allocative efficiency. This finding can be explained by the decreases in the price for natural gas in the United States due to fracking of shale gas (see Wang et al. (2014)). This price change renders input mixes which in addition to coal also contain gas more cost efficient than a production which is solely using coal. However, reaching this best practice is associated with adjustment costs which should be taken into account when analyzing the potential inefficiency and cost reductions.

Comparing the results for the two components, we find that the cost inefficiency is largely caused by allocative inefficiencies indicating that the plants operate with inefficient input mixes given the analyzed technology set. The numerical results as well as the dominating influence of the allocative inefficiency are in line with the findings of the previous literature. For example, Olatubi and Dismukes (2000) use cross-sectional data on U.S. power plants for the year 1996 and find an average cost efficiency of 65%, an average technical efficiency 93% and an average allocative efficiency of 66%.

Following Belu (2015), who argues that the technical efficiency should increase for DMUs with a modern capital stock, we also analyze whether the obtained technical efficiency results are plausible. Our comparison of the annual technical efficiency scores and the year of installment of the generating units shows an average correlation of 0.466 implying that our efficiency analysis leads to plausible results in the sense of Belu (2015). However, given the conventional approach to cost efficiency it is not clear whether the inefficiency is caused by rational behavior of the plants and whether the inefficiency can be exploited if adjustment costs are accounted for.

The remaining three panels of figure 2 present the average results of the decomposition of the cost efficiency and its components into rational and residual efficiency as well as the efficiency effect of technical change. In each panel the bold line represents the overall efficiency, while the rational efficiency is depicted by dashed lines, the residual efficiency is represented by dotted lines and the efficiency effect of technical change is indicated by the dot-dashed lines. The decomposition of the costs efficiency into rational and residual efficiency indicates an rational efficiency of approximately 90% implying an cost inefficiency of 10% can be explained by rational behavior. Stating differently, in the absence of adjustment costs the DMUs could decrease their costs by 10% if they exploit all available production possibilities in their individual technology set, hence without knowledge of the overall technology. The residual efficiency is about 70%. Therefore, the costs could be decreased by approximately 30% if this inefficiency is exploited and no adjustment costs are present.

The decomposition into technical and allocative rational and residual efficiency presented in the lower two panels shows the same patterns as the decomposition of the cost efficiency. Again, we find rational inefficiencies but a larger influence of the residual efficiency. Moreover, we find that the residual technical efficiency is very stable during the sample period and changes in the technical efficiency are solely caused by a decline in the rational efficiency. In contrast, the residual allocative efficiency increases while the rational allocative efficiency decreases. In particular, for the year 2009 we observe a drop in the rational allocative efficiency. This implies that the DMUs did not move to previous more gas-intensive input mixes due to unobserved adjustment costs. This result supports the finding by Abadie and Chamorro (2009) that changes in the fuel structure are also associated with significant costs. For both components, as well as the overall cost efficiency we find that the technical change component is very close or equal to one indicating that nearly no technical progress has occurred or that the plants were able to follow the technical progress. Since no substantial changes to the generating technology of the power plants (e.g. installment of new generators) can be observed in the data during the analyzed period, we interpret this finding as an indication of a lack of technical change.

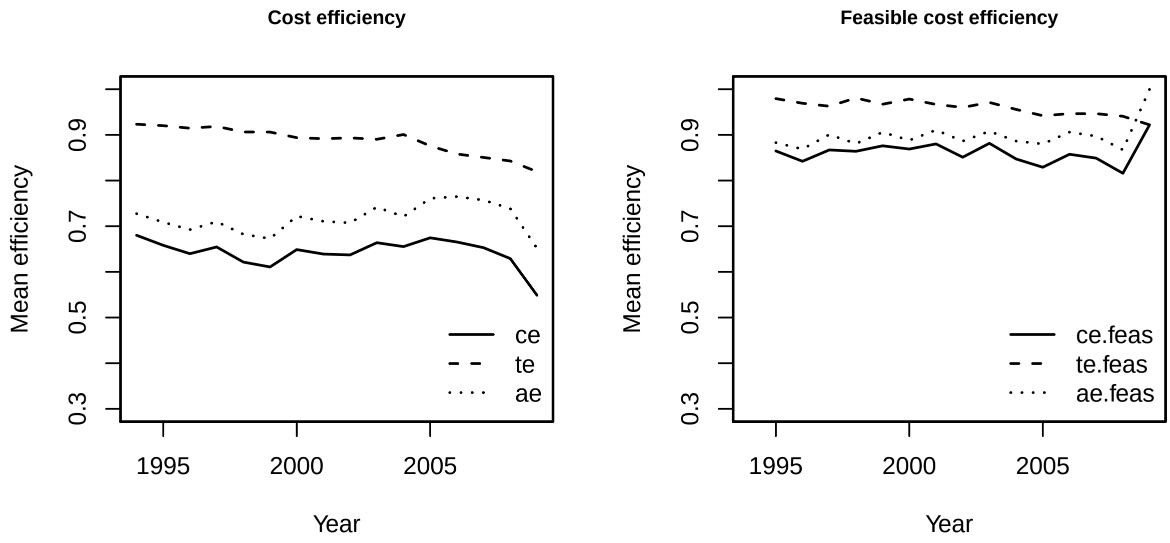

Figure 3: Results of feasible cost efficiency

Based on the results for the rational efficiency and the conditions (2.25) we evaluate whether the residual inefficiencies can be exploited if adjustment costs are accounted for. We assume that the costs are comparable across the power plants (see equation (2.20)) and test for linearity of the costs. The results of the test by Niermann (2007) are presented in table II in the appendix. For both cost types, technical and allocative adjustment costs, we find for the majority of years that the cost functions are linear. Only for the year 2005 we find that the technical adjustment costs are concave, while for the year 2009 we find evidence for a convex structure of the allocative adjustment costs. However, we note that the results for the feasibility are not largely influenced if the costs are assumed to be linear for all years.

The feasible cost efficiency as well as its decomposition are depicted in the right panel of figure 3. For a comparison, the left panel repeats the figure on the conventional analysis of cost inefficiency and the decomposition. The bold lines represent the cost efficiency, while the dashed (dotted) lines represent the technical (allocative) efficiency. The feasible cost efficiency is estimated based on the residual inefficiency which can be exploited if adjustment costs are accounted for. In this case, comparing both figures we find that the measured efficiency of the power plants is substantially increased. The overall cost efficiency is increased from 65% to 85% indicating that instead of 35% only 15% of the cost reductions can be exploited by adopting best practices. This symmetrically affects the radial and the non-radial input changes since the technical efficiency increases from 90% to 95% and the allocative efficiency increases from 70% to 88%. Moreover, we find that the obtained cost inefficiencies in the year 2009 due to decreased gas prices can not be exploited if the adjustment costs associated with reaching the benchmark.

4 Conclusion

In this paper we have presented a new approach to estimate rational inefficiency based on sequential definitions of production technologies. We further showed how lower bounds on technical and allocative adjustment costs can be obtained by evaluating unexploited cost reductions based on individual input sets. These lower bounds can be used to quantify the extend of feasible cost reductions if adjustment costs are taken into account. Compared to previous models on rational inefficiency, our model does not attribute all inefficiency to either entirely rational or non-rational behavior but allows to decompose the overall inefficiency into rational and residual inefficiency. In contrast to approaches based on dynamic optimization, our model depends on less restrictive assumptions regarding the behavior of the DMUs and and provides a completely nonparametric approach to estimate and decompose the rational inefficiency as well as to analyze the feasibility of cost reductions in the presence of adjustment cost.

Applying our model to a sample of coal-fired power plants in the United States we found that approximately 10% of the 35% of inefficiency can be explained by rational behavior. The rational and the residual inefficiency are largely caused by allocative inefficiency indicating that most plants operate with inefficient input mixes. In contrast, the technical efficiency with regard to both components is relatively high. Moreover, we found that nearly no technical progress occurred within the analyzed period from 1994 to 2009 showing the technological frontier of the plants has not exhibited large shifts during this period. Taking into account adjustment costs, we found that the cost inefficiency decreases from 35% to only 15%. This shows that previous studies which obtained comparable numerical results based on a conventional approach to cost efficiency significantly overestimate the possibilities to reduce costs in the generation of electricity. Therefore, our results imply that analyses which are based on evaluating cost inefficiencies (e.g. studies on the benefits from mergers in the electricity sector, see Kwoka and Pollitt (2010)) may lead to biased results and policy implications if rational inefficiencies and adjustment costs are not taken into account.

However, we want to stress that our findings are only based on the relatively small number of 37 power plants. While this sample size is comparable to the number of analyzed plants in previous studies, it nonetheless provides limits to the generalizability of the results on rational inefficiency of power plants. Therefore, future research may evaluate whether the found efficiency patterns can also be obtained using plant data from different countries (e.g. data for Japanese power plants as analyzed in e.g. Goto and Tsutsui (1998)). Furthermore, in this study we discuss how our theoretical model can be applied using nonparametric DEA methods to estimate the technology sets and efficiency measures. Alternatively, parametric models which account for statistical noise could be applied. Future research may follow Park and Lesourd (2000) and compare the results based on parametric and nonparametric techniques to evaluate to which extent the rational and residual inefficiency, as well as the feasibility of the cost reductions, are influenced by random effects. Finally, our methodology could be extended by including a frontier separation approach (see Charnes et al. (1981)) to differentiate the rational inefficiency for several subgroups (e.g. power plant types) within the overall technology.

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Appendix

Table II: Results of the Niermann (2007) test of linearity

H_0 : Technical adjustment costs are linear								
	1995	1996	1997	1998	1999	2000	2001	2002
Test statistic	1.164	0.329	-0.830	-0.563	0.621	-0.840	1.431	0.721
p-value	0.244	0.742	0.407	0.573	0.535	0.401	0.153	0.471
	2003	2004	2005	2006	2007	2008	2009	
Test statistic	-0.885	-0.041	-1.686	1.199	-0.222	0.671	1.233	
p-value	0.376	0.967	**0.092**	0.230	0.825	0.502	0.218	
H_0 : Allocative adjustment costs are linear								
	1995	1996	1997	1998	1999	2000	2001	2002
Test statistic	1.326	1.030	0.714	-1.638	0.152	-0.443	-0.577	0.718
p-value	0.185	0.303	0.475	0.101	0.879	0.658	0.564	0.472
	2003	2004	2005	2006	2007	2008	2009	
Test statistic	0.988	0.005	0.002	0.398	0.517	0.952	2.015	
p-value	0.323	0.996	0.998	0.691	0.605	0.341	**0.044**	

Note: Statistical significant results (p-values less than 0.1) are indicated in bold.
The null hypothesis of non-concave technical adjustment costs was rejected in 2005 (p-value: 0.046).
The null hypothesis of non-convex allocative adjustment costs was rejected in 2009 (p-value: 0.022).