Essays on Efficiency Measurement and Corporate Social Responsibility

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Paper 1: Ranking corporations based on sustainable and socially responsible practices. A Data Envelopment Analysis (DEA) approach

This study ranks publicly listed corporations based on social and environmental (i.e. sustainable) achievements in relation to financial results, by using a Data Envelopment Analysis (DEA) approach with financial performance indicators (return on assets, return on equity and yearly stock return) as inputs and sustainability scores as outputs. The sustainability scores cover a wide range of sustainable practices and were provided by a specialized screening company. Our calculated DEA indices provide a measure of the commitment of firms towards sustainable practices. The main findings are that many companies are positioned well below best practice in their respective industries. Industry sectors that are less scrutinised by the public (e.g. banking) are found to be less competitive in terms of sustainable practices.

Paper 2: Strategic Corporate Social Responsibility and Economic Performance

This paper studies the link between Corporate Social Responsibility (CSR) and economic performance of companies. Acknowledging the argument that companies might behave socially responsible strategically, i.e. favoring the CSR dimensions that provide competitive advantages, we construct a novel CSR index based on a Data Envelopment Analysis (DEA) model. We argue that this index accounts for CSR achievements from a strategic perspective, and use it to analyze the link between CSR and economic performance expressed by Return on Assets (ROA). When explicitly accounting for strategic behavior of companies, our findings reveal a significant positive relationship between CSR and economic performance.

Paper 3: The effect of IT capital on the efficiency of Swedish banks

This paper investigates the impact of Information Technology (IT) capital on the technical efficiency of Swedish banks against the background of the so-called "productivity paradox," which puzzled economists in the 1990s. Panel data of 85 banks observed during 1999-2003 is used for this purpose. Employing a stochastic frontier production function that allows for time-varying technical efficiencies shows that the technical efficiency of Swedish banks increased with the amount of employed IT capital.

Paper 4: Are all DMUs efficient in DEA? DEA meets the vintage model.

In this paper I develop a model of capacity expansion that accounts for differences in the productivity of the installed capital due to technical progress exhibited by the *ex ante* production function. A putty-clay set-up is assumed, meaning flexible input coefficients and substitution possibilities *ex ante*, but fixed input coefficients *ex post*. Based on the model, I generate a capacity distribution of DMUs (vintages) for a homogenous industry and perform an efficiency analysis employing data envelopment analysis, a popular non-parametric method for estimating efficiency. The results show that in some circumstances older vintages might appear on the efficiency frontier, unlike some newer vintages that are found to be inefficient, despite benefiting from the advancement of the technology.

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"To educate a man in mind and not in morals is to educate a menace to society".
Theodore Roosevelt

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Overview

This thesis consists of four free-standing papers. The unifying element is the resort to parametric and non-parametric techniques traditionally developed for the measurement of economic efficiency and economic performance. In addition, in the first two papers I use Data Envelopment Analysis (DEA) in a novel manner in order to construct numerical measures for Corporate Social Responsibility (CSR).

Paper 1 reviews the traditional difficulties encountered when analyzing the potential link between corporate social performance and economic performance. It then proposes the construction of a new measure for CSR, resorting to DEA, a widely used management tool. The measure does not necessarily hypothesize a link between CSR and economic performance, but it nonetheless provides insights with regard to CSR achievements in certain industrial sectors. The main finding is that industries that are less scrutinized by the public, e.g., the banking industry,[1] are prone to poorer socially responsible behavior.

Paper 2 (co-authored with Cristiana Manescu) exploits a specific feature of the DEA technique, namely the construction of aggregate indices for performance with variable, endogenously determined sets of weights. We construct a novel measure for CSR, using DEA, and argue that this measure also accounts for the strategic behavior of companies with regard to socially responsible measures. In a subsequent step, we use the constructed CSR index as an explanatory variable in a dynamic panel data model for Return-on-Assets. The findings suggest a persistently positive link between strategic CSR and the economic performance of companies.

Paper 3 investigates the impact of Information Technology (IT) capital on the technical efficiency of Swedish banks against the background of the so-called "productivity paradox," which puzzled economists in the 1990s. Panel data of 85 Swedish banks observed during 1999-2003 is used for this purpose. Employing a stochastic frontier model with two alternative specifications for the efficiency effect, it is found that IT capital has a positive effect on the technical efficiency of Swedish banks. This finding adds to the growing evidence of the importance of IT capital in productivity growth.

Paper 4 confronts a putty-clay model of capacity-expansion, generating a capacity distribution of different vintages of decision-making units, DMUs, with the efficiency scores obtained by DEA for each set of DMUs generated by the model under different assumptions about technical progress, demand growth, elasticity of scale and relative price changes. The main finding is that DEA is not able to retrieve distributions of efficiency corresponding to the respective vintage distribution.

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[1] This was at least the case at the time of writing. As a result of the current financial crisis, the public's attention has probably changed its focus, scrutinizing more closely the banking sector.

Paper I

Ranking Corporations Based on Sustainable and Socially Responsible Practices. A Data Envelopment Analysis (DEA) Approach

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ABSTRACT

This study ranks publicly listed corporations based on social and environmental (i.e. sustainable) achievements in relation to financial results, by using a data envelopment analysis (DEA) approach with financial performance indicators (return on assets, return on equity and yearly stock return) as inputs and sustainability scores as outputs. The sustainability scores cover a wide range of sustainable practices and were provided by a specialized screening company. Our calculated DEA indices provide a measure of the commitment of firms towards sustainable practices. The main findings are that many companies are positioned well below best practice in their respective industries. Industry sectors that are less scrutinized by the public (e.g. banking) are found to be less competitive in terms of sustainable practices. Copyright © 2009 John Wiley & Sons, Ltd and ERP Environment.

Introduction

THERE IS A CONSIDERABLE BODY OF RESEARCH CONCERNING FIRMS' ADOPTION OF SOCIALLY AND ENVIRONMENTALLY sustainable practices. One path followed by researchers in this field is to investigate whether improvements in financial performance are correlated with environmentally and socially responsible company conduct. If a positive correlation is found, then a strong argument in favour of a sustainable conduct in terms of environment and society is passed to the corporate world. The next section of this paper provides a review of the main strategies adopted in the empirical research on the nature of the relationship between sustainability achievements and financial performance. It also provides reasons why such a relationship may be very difficult to reveal.

This paper proposes a tool for analysing the above mentioned relationship from a different perspective. By considering a sample of large corporations listed on the major stock exchanges, we construct a relative measure of performance based on the trade-off between economic and financial performance and social responsibility or sustainability. We are then able to identify best practice through a fair comparison between the companies at hand. The companies found to belong to the best-practice set in terms of sustainability are the companies that achieve the best social and environmental standards, conditional on their financial results.

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In the light of recently emphasized environmental threats, knowing which companies are the most successful in terms of environmental practices is of utmost importance. Moreover, the global trend to transfer state-administered pension funds to private administrators creates a huge pool of investment funds with a long-term objective. For these administrators, selecting a portfolio of fair companies in terms of social responsibility will probably be an important goal. The multi-dimensionality aspect of corporate social and environmental performance might make the task of choosing the right companies very difficult. The purpose of this paper is to facilitate this selection.

One problem arises when we attempt to formalize the definition of corporate social performance (CSP) or corporate social responsibility (CSR). According to Business for Social Responsibility,[1] one definition could be '… achieving commercial success in ways that honour ethical values and respect people, communities and the natural environment'. There are other alternative but similar definitions as well.[2] Regardless of which definition we accept, one important aspect is already revealed: the multidimensional nature of the problem. A meaningful formalization has to account for variables that describe dimensions such as corporate governance, codes of conduct with respect to corruption and bribery, human capital development, labour practice indicators, environmental performance/management, reporting practices etc.

One very convenient way to deal with multiple variables is provided by data envelopment analysis (DEA), a management tool that has been used extensively to measure performance and best practices in a given population of units (firms, etc). DEA copes very well with multiple input/multiple output processes. It is a non-parametric multivariate method based on linear programming, which has proven its efficiency in uncovering relationships that remain hidden for other methodologies, especially when no clear profit objectives are in place.

DEA is suitable for our proposed analysis since, while there is a debate on which social and environmental dimensions should be emphasized in a CSP index, and accordingly be awarded a higher weight on aggregation, DEA constructs an endogenous set of weights by letting them be determined as part of an optimal solution to a formal aggregation problem. In other words, DEA assigns a particular set of weights to each firm, awarding higher weights to those dimensions where a firm scores better. It has been said that the DEA index casts each firm in the best possible light, and this property allows for comparisons between firms with different business profiles. Moreover, DEA provides the means to identify in which dimension one particular firm is lagging behind best practice, and it gives precise quantitative qualifications to the sub-optimal level; hence it gives the percentage by which a particular sub-optimal firm should improve in a certain dimension to achieve the best practice.

The remainder of the paper is organized as follows. The following section provides a review of the competing views concerning the relationship between sustainability achievements and economic/financial performance, and attempts to provide some insights on why it is not a conspicuous relationship. The next section provides a brief description of DEA modelling and of the assumptions on which the use of DEA rankings in the field of social and environmental performance are based. The fourth section describes the data used in the present study. The fifth section presents the results obtained from analysing the available data set, and then comments on these results. The sixth section sets forth conclusions and signals a number of potential shortcomings of our approach together with their remedies.

Empirical Studies on the Relationship Between CSR and Economic Performance

There is a considerable stream of literature on the link between sustainable practices and economic/financial performance of companies. To reveal the relationship between financial and social or environmental performance, different methodologies have been used: *event studies*, assessing market response after a positive or negative information release concerning social or environmental issues (Hamilton, 1995; McWilliams *et al.*, 1999); *portfolio* or *SRI (socially responsible investment) fund screening studies*, comparing SRI fund performance with non-SRI oriented funds/portfolios (e.g. Hamilton *et al.*, 1993; Cohen *et al.*, 1997), and several *multiple regression analyses* that have

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[1] Business for Social Responsibility is a non-profit business association headquartered in San Francisco and specialized in providing socially responsible business solutions to global enterprises.
[2] One definition proposed by the European Commission (2001) is the following: 'CSR is a concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with stakeholders on a voluntary basis'.

tried to assess the influence of sustainable measures on the economic performance of firms or the other way around (the impact of economic performance on sustainability indices) (Hart and Ahuja, 1996; King and Lenox, 2001; Waddock and Graves, 1997).

Most of the studies, however, focus on one or several dimensions related to sustainable behaviour, such as stakeholder activism, corporate governance, human resource practices, labour relations and community relations. A detailed study aimed at capturing the impact of corporate governance practices on equity performance and other firm characteristics was made by Brown and Marcus (2004). Barnett (2007) proposes a few hypotheses and concepts (e.g. 'stakeholder influence capacity') to help understand the relationship between stakeholder relations and corporate social responsibility. He suggests that corporate social responsibility should be assessed on a firm by firm basis and not universally. Stakeholder activism is analysed empirically in relation to financial performance by Shawn *et al.* (1999). As a proxy for stakeholder relationship, KLD[3] measures concerning local communities, workforce diversity, employee relations or natural environment are used. Both direct effects and interactions are analysed through multiple linear regressions. The main finding is that the relationship between stakeholder orientation and corporate social responsibility is too complex to be explained by a direct effect model.

A fairly large number of studies are concerned with the link between natural environment interaction and the economic performance of firms (Filbeck and Gorman, 2004). Cohen *et al.* (1997) create a high- and a low-polluting portfolio of S&P500 companies, and show that there is either no distinction in terms of economic performance between the two different portfolios, or, when there is, it is in favour of the low-polluting one. Derwall *et al.* (2005) have a rather similar approach and conclude that there is a premium for investing in the higher-ranked portfolio (based on environmental rankings provided by Innovest[4]), even when accounting for transaction costs. Hart and Ahuja (1996) conclude through an analysis at the company level that it pays to be green, whereas King and Lenox (2001) assert that, while there is a relationship between environmental and financial performance, no clear conclusion related to its direction can be made.

There are several reasons why there might not be a simple pattern between social and environmental achievements and financial performance. Stakeholder structure and interests vary, and this is reflected in the different ways of managing a company (Barnett, 2007). These interests can vary from strictly profit-oriented interests of short-term investors to sustainable long-term commitments of institutional investors or involvement of powerful labour unions in managerial decisions. These conflicting interests are translated into a variety of patterns for the relationship between financial performance and sustainable social and environmental achievements.

Perhaps the most difficult problem for empirical studies on CSR is the very different impacts that various CSR dimensions might exert on businesses with different profiles. The technology sector usually scores very well when it comes to dimensions such as human capital, while at the same time being able to achieve good financial performance. This situation might induce one to wrongly conclude that there is a positive relationship between financial performance and sustainable behaviour. However, it would be less likely to find the same result for, say, the mining sector.

Related to the above arguments, Cerin and Dobers (2001) signal a bias for the indices constructed to track sustainable companies, such as the Dow Jones Sustainability Group Index (DJSGI). The bias is due to the tendency to include more companies from the technology sectors in the sustainability indices, raising some legitimacy questions regarding the studies using these indices to infer links between financial performance and sustainability. This argument applies to the banking and financial services industry as well.

Why is the Relationship Between CSR and Economic Performance So Intricate?

A number of competing theories have been proposed in the literature as to what kind of relationship one might expect to find between financial and economic performance on one hand and the sustainability achievements of an enterprise on the other. A comprehensive review of the alternative theories and the related literature is given by Wagner *et al.* (2001).

[3] KLD is the abbreviation for Kinder, Lydenberg, Domini and Co., a US-based rating agency whose scores are widely used in empirical studies related to corporate social responsibility.
[4] An investment research and advisory firm specialized in analysing the impact of companies' environmental and social performance on their financial performance.

Porter and Van der Linde (1995) suggest that better environmental practice might generate a competitive advantage when it is accomplished through innovative technologies; input costs will be lowered and productivity increased (the revisionist economic view introduced through the much cited *Porter hypothesis*; Porter, 1991).

A second competing view is that stringent corporate social responsibility regulation (especially concerning environmental regulation) is believed to lead to high compliance costs for companies, with some industrial sectors being more severely affected (e.g. oil and gas). This in turn induces a competitive disadvantage for certain companies with higher compliance costs. The work of Cohen *et al.* (1997) is an example of this view, labelled as the traditional microeconomics view (i.e. higher costs, lower profits).

Wagner *et al.* (2001) propose a synthesis of the two above-mentioned views materialized into an inverse U-shaped relationship between economic performance and social and environmental performance. According to their proposal, the benefits reaped from increased environmental performance increase continuously for low levels of environmental performance up to a certain point around or slightly above the average environmental performance. After this, the relationship is likely to be represented by a downward-sloping curve.

Finally, I propose a dynamic perspective on the discussed relationship. It is likely that in the short run, and for most firms, increasing efforts towards better social and environmental (S&E) practices will increase costs too. This is translated into a negative relationship between S&E achievements and financial results. However, the increased efforts to improve corporate governance practices, to acquire production standards and to implement schemes of pollution reduction will probably, in the long run, lead to better company performance and to above industry-average financial results. I am not aware of any empirical studies concerning this view. One reason might be that this kind of study requires cross-sectional time series data, and data sets concerning sustainable practices are rather scarce.[5]

There are a variety of additional reasons why it might be difficult to properly assess the relationship between economic/financial performance and sustainable social and environmental achievements, for example related to methodology, the data used or a lack of properly defined standards.

It is interesting, however, to summarize the main channels through which CSR might impact firm economic activity. Four major channels through which relations of causality between CSR and economic performance can be established are identified. To properly define these channels it is useful to distinguish between economic
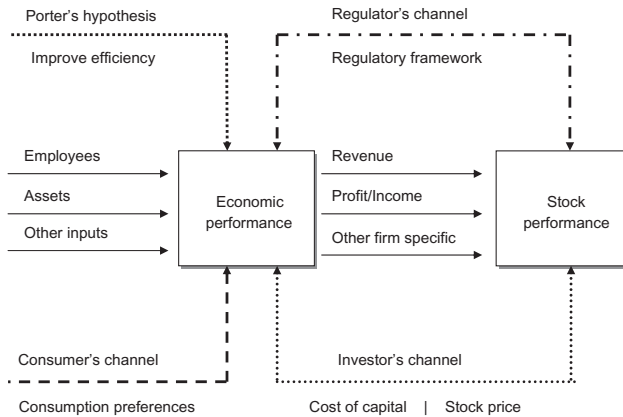

Figure 1. The channels of interaction between CSR and economic and stock market performance

[5]Another serious drawback could be the fact that companies actively engaged in increasing their sustainability scores are likely to be at different stages of implementing their policies to improve their sustainability practices, and this is difficult to disentangle without proper information.

Environmental dimensions	Social dimensions	Governance dimensions
Environmental performance	Labour practice indicators	Corporate governance
Environmental reporting	Human capital development	Risk & crisis management
Waste management	Corporate citizenship/philanthropy	Codes of conduct/compliance
	Social reporting	Corruption & bribery
	Human rights	Talent attraction & retention

Table 1. The most common dimensions evaluated by rating agencies

performance and stock market performance of a company, as shown in Figure 1 and explained in detail in the next paragraph:

The first channel through which CSR might impact the core business is through efficiency and productivity gains, as emphasized by Porter (1991). Active CSR measures might in turn enhance organizational efficiency and lead to gains in productivity. The second channel, or the consumer channel, allows consumer preferences to play a role in enhancing the firm sales (e.g. preferences for 'green' products). Hence an active CSR policy might in turn improve economic performance of the company. The third channel allows the regulator to alter firm economic and stock market performance through adjustments of the regulatory framework in response to the firm's CSR attitude; i.e., firms with proven CSR records might benefit from favourable regulation and this in turn might give them a competitive advantage. Finally, the investor channel is the way investors and stockholders might add value to a CSR firm: through raising the price of stocks and through lowering the cost of capital for the respective firms.

It should now be clear that the relationship between economic performance and the CSR of a company is intricate and involves various stakeholders and different channels through which CSR might have positive spillages for the economic performance of companies. Consequently, a great number of empirical studies have been conducted in this field.

Given the mentioned theoretical and practical difficulties encountered when assessing the relationship between CSR and economic performance, I propose a sidestep from the descriptive perspective. This approach should be useful not only for researchers and practitioners interested in screening for sustainable companies, but also for companies themselves in identifying their weak/strong points in terms of sustainability.

DEA provides a powerful tool for a proper ranking of companies in a fair and objective manner, based solely on the available data. It remains, however, the analyst's decision to specify what dimensions should be considered relevant when assessing sustainability. It is worth noticing that these can change in time, in accordance with social norms and new priorities.

Broadly, three main directions are considered when assessing the sustainability of a corporation: *environment*, *society* and *governance*. This clustering of the relevant sustainability criteria has come to be known as the ESG paradigm, and most specialized rating agencies choose to survey and award marks (scores) to the dimensions shown in Table 1.[6]

Model Description

DEA is a performance measurement tool that has been extensively studied and used in empirical applications. It started with the model proposal by Charnes *et al.* (1978), or the *CCR model*. Farrell (1957) also used non-parametric piecewise linear frontiers for efficiency measurement.

DEA addresses processes with multiple inputs and outputs developed through a decision-making unit (DMU). The most natural example of a DMU is a productive firm, but the entities that have been assimilated to DMUs in empirical applications vary widely. DEA is especially appropriate when there is no clear profit maximization

[6] For example, see KLD methodology at http://www.kld.com/research/ratings_indicators.html and SAM methodology at http://www.sam-group.com/

objective for the DMUs under scrutiny, e.g. schools, universities, hospitals, public administration units, and even bank branches within the same bank. It is really useful for the service sectors, where it is more difficult to define a clear objective or a generally accepted standard.

The novelty and key issue of this paper is the way in which it chooses to link the sustainability achievements of a company to its financial and economic performance. DEA has mainly been employed in an input/output framework, where inputs are entries into a production process (e.g. raw materials, labour, energy etc.) and outputs usually are physical quantities of goods in the manufacturing industry or clients serviced in the service sector.

This paper proposes to consider as inputs the economic and financial results of a particular company and as outputs the sustainability achievements of this company, as given by the marks awarded by the specialized screening companies, for each dimension of interest. Hence, our 'production' process is the conversion of economic results into socially and environmentally sustainable achievements. This is, of course, an 'alternative' production process, as many companies do not set as their main objective the optimization of this process of transformation. It nonetheless describes the commitment of companies to social and environmental values, and this process can be characterized by various degrees of success or failure, and, more importantly, it can be described in terms of efficiency, as by Farrell (1957).

Moreover, this approach is very handy for comparing heterogeneous datasets, i.e. companies with different economic profiles from various industries, as is done when constructing a stock market index or a well balanced portfolio of companies (which should be of importance to financiers). It does, however, preserve industry-specific features and can be used in assessing the degree of success within a particular industry, and it can be used to calculate company-specific efficiency scores and perform meaningful rankings of companies with very different economic backgrounds.[7] What this sort of approach reveals is the commitment of various corporations to achieve long-term sustainability with respect to economic, environmental and social criteria.

How Does DEA Work?

Many scholars have contributed to the development and refinement of DEA techniques. DEA has been tuned to fit a wide range of practical applications, and numerous specialized software packages have been released. The following brief presentation of DEA is based mainly on the work of Cooper *et al.* (2000).

DEA forms a virtual input and a virtual output for each DMU by using a set of (unknown ex ante) weights:

$$\text{virtual input} = v_1 x_{1o} + \ldots + v_m x_{mo}$$
$$\text{virtual output} = u_1 y_{1o} + \ldots + u_s y_{so}$$

where v and u are weights and x and y are inputs and outputs, respectively.

The next step is to determine the optimal input weights v_i, $i = 1, \ldots, m$ and optimal output weights u_r, $r = 1, \ldots, s$ for each DMU_j, using linear programming techniques, so as to maximize the ratio

$$\max \theta = \frac{u_1 y_{1k} + \ldots + u_s y_{sk}}{v_1 x_{1k} + \ldots + v_m x_{mk}}$$

$$subject\ to$$

$$\frac{u_1 y_{1j} + \ldots + u_s y_{sj}}{v_1 x_{1j} + \ldots + v_m x_{mj}} \leq 1 \quad j = 1, \ldots, n$$

$$v_1, v_2, \ldots, v_m \geq 0$$
$$u_1, u_2, \ldots, u_s \geq 0$$

[7] One important aspect should be mentioned here. In fact, it derives from the way industry heterogeneity is addressed. Based on discussions with practitioners in sustainability ranking, one way to address the problem is to construct different questionnaires (containing specific questions for each industry). Companies belonging to one industry fill in their specific questionnaire, based on which an overall mark is calculated for each dimension (e.g. eco-efficiency). This way, the resulting scores are directly comparable, regardless of the industry, and can be considered for the construction of an overall index of sustainability (DEA can be used directly). Another way is to actually construct different indices for each industry, by including industry-specific dimensions, or award different weights in the aggregation, that is, industry-specific weights. In the latter case, a DEA index has to be computed for each industry. Although this will make it more difficult to make cross-industry comparisons, recent advances in the DEA methodology show how it can be done (Edvardsen, 2004).

Hence, the optimal weights may vary from one DMU to another. This is an objective process of deriving the optimal weights from data, instead of fixing them in advance. It is important to realize that there is a ratio for each DMU, so we will obtain N maximal values (θ^*) and N optimal sets of weights if there are N units in the sample. The ratio θ^* is restricted to be less than or equal to unity, and for the units that have a $\theta^* = 1$ after optimization, we say that they are optimal, i.e. performing best. The smaller the calculated θ^*, the more inefficient the corresponding unit.

The weights used for calculating each ratio are chosen (they emerge from the optimization process) as the weights that shed the best light on each corresponding unit, in the sense of maximizing the associated ratio. If v_i^* is the optimal weight for input i ($i = 1, \ldots, N$), then its magnitude shows how highly that input is valued when constructing the aggregate index of efficiency.

In our application, some of the input values are negative, i.e. *return on equity, return on assets* and *average stock returns* may have negative values. DEA accommodates only non-negative inputs, since it considers inputs as mandatory for the production process. I then need to perform a transformation of our data. I shall perform an affine transformation (translation) of the inputs only. While the model presented above is not translation invariant, we know that the BCC model (Banker *et al.*, 1984) is partially translation invariant, in the sense that it is invariant to a translation in inputs or in outputs, but not in both simultaneously (Lovell and Pastor, 1995). Consequently, the computed DEA scores are based on the BCC model. Fortunately, I only have to deal with negative inputs, as all the outputs are positive. Hence, we will add a positive absolute value to every input level x_j. The scaling value will be equal to the maximum absolute value for each input before transformation.

DEA models are devised as *input oriented* (IO) or *output oriented* (OO). The distinction comes from the way adjustments are made to inefficient units in order to obtain their efficient projections. If adjustments are made in the input space, we have the *input-oriented* approach. If adjustments are made in the output space, then we are talking about the *output-oriented* models.[8]

An *output-oriented* model aims at maximizing the output levels under, at most, the present input consumption. In our study, the output is given by the bulk of *socially responsible* and durable variables, while inputs are the variables describing the financial performance of the firms (i.e. *return on equity, return on assets, average stock returns*). Since I want to find out whether corporations 'achieve' enough given their financial status or whether they can improve their achievements, choosing an *output-oriented* model seems natural. Moreover, since I have to perform a translation of our inputs in order to deal with their negative values, we know that the BCC *output-oriented* model is invariant with respect to a translation in inputs. Consequently, this is the model that I shall use.

Data

The dataset contains financial performance measures for a sample of 1012 large corporations listed on the world's main stock exchanges and sustainability scores for the same companies, provided by a leading sustainability-rating agency.[9] *Return on assets (ROA), return on equity (ROE)* and *average (yearly) stock returns (ASR)* are included as financial performance measures. The sustainability scores describe the following dimensions: *corporate governance, environmental performance, human capital development, labour practice indicators* and *social reporting*. These scores were calculated following the completion of a questionnaire comprising detailed questions regarding a number of dimensions considered relevant for CSR. Table 2 below gives descriptive statistics for the variables used in this study.

I shall consider financial performance measures as inputs and sustainability scores as outputs, in accordance with the traditional DEA methodology. Recall that this does not imply any causal relationship between the mentioned dimensions. I simply scrutinize the degree of sustainable achievements against the financial performance background.

Sustainability scores are calculated on a scale from 0 to 100, with 100 representing maximum achievement for that particular dimension.

[8] There is a third choice, i.e. models that simultaneously adjust both outputs and inputs – the so-called *additive* models with their *slack-based* variants.
[9] Our data provider is SAM, a Zurich-based independent asset management company specialized in sustainable investments. The financial data come from Thomson Datastream.

Variables*	Mean	Std dev.
Inputs		
ROE	16.49	18.40
RTA	6.37	6.32
ASR	0.16	0.24
Outputs**		
Corporate governance	70.03	12.80
Environmental performance (eco-efficiency)	27.90	33.89
Human capital development	25.01	26.43
Labour practice indicators	58.37	15.50
Social reporting	48.49	34.09

Table 2. Summary statistics
*2005 values, after removing outliers.
**These are scores from 0 to 100 calculated by a specialized screening company; 100 represents maximum achievement.

Obtained Efficiency Scores and Some Comments

A large degree of variation is found in the efficiency scores, indicating that there is room for improvement. Many companies are sub-optimal, meaning that, given their financial achievements and good economic results, they simply do not do (achieve) enough when it comes to sustainable social and environmental practices.

The set of *best practice* units describes a hyper-plane (frontier) that envelops all the other units (hence the name of the technique). The absolute values of scores in the *output-oriented* framework indicate the departure from the frontier and implicitly from the *best practice*. They also show the potential for improvement, i.e. by how much a sub-optimal firm should increase its output while maintaining the same level of inputs, in order to achieve the *best practice*.

Best practice means a score of unity. The closer to unity, the more efficient a firm is.[10] *Best practice* describes a set of companies that manage to achieve the most, relative to the set of units under scrutiny. Hence, it is a relative measure of efficiency, relying heavily on the quality of the data used. It is also sensitive to sampling bias, error measurement and outliers. However, remedies for these problems have been proposed in the literature (Simar and Wilson, 2000; Simar, 2007).

Several empirical studies have signalled that different social and environmental achievements might have different implications for a firm's economic and financial performance, i.e. improvements in some dimensions are likely to have stronger impacts on the economic results. DEA provides precise quantitative indicators for each unit (company) regarding the magnitude of improvement needed for each social and environmental dimension where it lags behind *best practice*. These scores should be useful for managers interested in socially responsible norms that can be improved upon. However, this approach cannot quantify the direct economic gain.

Figure 2 shows the average efficiency score for each sector when a common frontier is used. This means that companies from different industries are used to construct the efficiency set, i.e. a common frontier, and then the average efficiency for each sector is computed. In this set-up, the most efficient companies appear to belong to the 'industry' sector (manufacturing included) and to 'technology'. Surprisingly, the 'financial' sector appears to perform the worst. The reason is that companies from the financial sector usually report very good economic and stock market results, while their reported environmental, social and governance practices are not equally good. This does not necessarily imply that they perform badly on any of the sustainable practices included in the analysis (at least not worse than industrial companies), but in relative terms they do not achieve as much as they should,

[10] In fact, in the *output-oriented* framework, most software packages construct an efficiency ratio greater than unity, with unity corresponding to the least efficient companies. The higher the computed value, the more efficient the corresponding unit. I make the appropriate transformations in order to have the ratio converted to the (0, 1] interval.
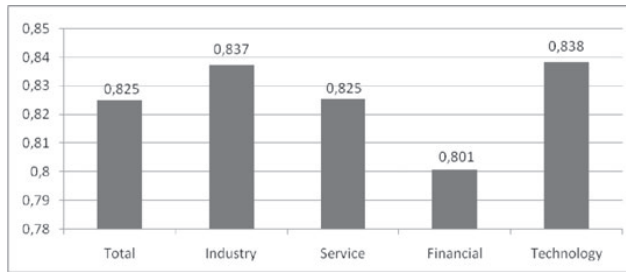
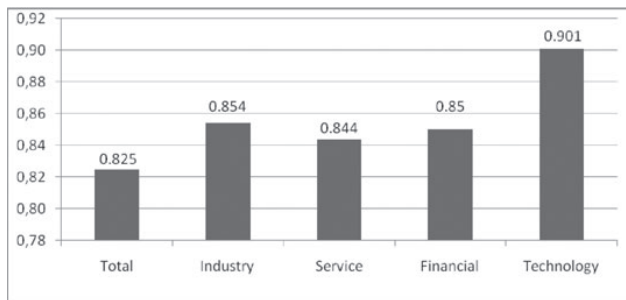*Figure 2.* Mean efficiency for each sector. Common frontier

Figure 3. Mean efficiency for each sector. Industry specific frontiers

given their resources. Remember that in this case the 'resources' are given by the economic and financial results, i.e. return on equity, return on assets and stock market returns. Also, recall that companies share the same sets of inputs and outputs, even if they belong to different industries.

A second analysis considers industry-specific frontiers (Figure 3). The average scores for each sector are relative to that sector. Again, the financial sector appears slightly less efficient than *technology* and *industry*. *Technology* performs the best. The total average is still calculated for the whole sample, which is the case with a common frontier. On average, while each particular sector appears to be more efficient than under the common frontier, it is easy to see that the most efficient companies belong to the *technology* sector. This confirms the fear that sustainability indices such as the Dow Jones Sustainability Index might induce a composition bias when used to study the relationship between financial performance and sustainability achievements (Cerin and Dobers, 2001).

Figure 4 shows the distribution of efficiency scores within industries. The large variation in the calculated scores shows that there is considerable potential for improvement, i.e. a significant number of companies can achieve more in their sustainable social and environmental practices.

The results described above are relevant for policy making. They show that there is an important potential for improvement in the efficiency of the *financial* sector, meaning that financial companies could achieve more in terms of sustainable practices. However, this result is expected considering that the financial sector faces far less pressure to behave sustainably. In fact, sustainable standards are not even clearly defined for this industry. Banks, for instance, usually undertake 'cosmetic' measures such as recycling or using bio-fuels for heating. This is insignificant in comparison with the amount of abatement expenditure incurred in other industries. A more socially
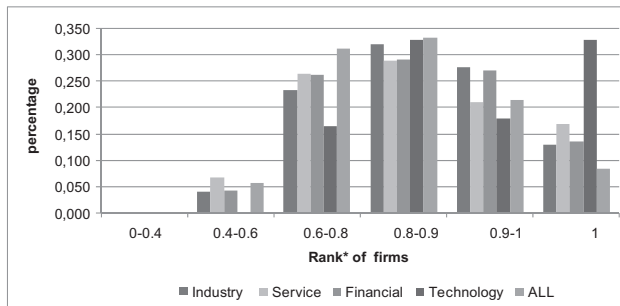
*The rank gives the relative efficiency and is between 0 and 1. In an output oriented framework, a 1/rank indicates by how much a firm should increase *all* outputs to become efficient.

Figure 4. Percentage of firms per efficiency intervals for each industry

responsible approach would be to provide favourable lending rates for the sustainable businesses in their portfolios, for instance.

The most valuable contribution of this approach is that it reveals relative performance scores for each company. These scores allow the selection of the best performing companies, which in turn can be used to construct stock portfolios or stock market indices.[11]

Conclusions

This study proposes a tool for obtaining information about firm engagement in sustainable activities. Index numbers are calculated based on a DEA output-oriented model, and describe the success of the companies in terms of sustainable behaviour. The study is, to my knowledge, a novelty in the sustainable development and CSR literature. Shadbegian and Grey (2006) resort to a frontier approach to assess multidimensional environmental performance, but they use a stochastic frontier instead of DEA. Bosetti and Locatelli (2006) employ DEA to assess the economic efficiency and sustainability of natural parks.

The approach used in the current paper is to consider economic and financial achievements of a company as exogenously given variables, and then to look at the sustainable practices of that particular company as given by its sustainable scores calculated by an independent agency. The more a company does in terms of sustainability, the better its DEA score. The DEA approach is intended to end the debate about which weights should be assigned to different dimensions of sustainability and social responsibility.

Among the interesting findings is that the financial sector does not perform very well compared with, for example, the primary industry sector. The explanation for this is that firms from the financial sector (banks, insurance companies etc.) usually report very good economic results, while performing averagely in most of the sustainable dimensions investigated here. This is a sensible point. Although it does not mean that they do badly in absolute terms, we can say that they do not achieve enough given their excellent 'inputs' (i.e. economic results).

This finding is perhaps connected with the debate regarding who is going to bear the heaviest burden involved in alleviating the environmental pollution output. Sectors that contribute less to environmental pollution are generally less scrutinized by the public opinion and this in turn translates to poorer socially responsible practices. Overall, it is found that most industries deviate significantly from best practice in terms of social responsibility.

[11] Due to confidentiality requirements, I do not report company-specific scores in this paper.

One shortcoming of this study is the static picture that emerges from it. With only a cross section at hand it is no doubt a useful approach, but not much can be said about the dynamics of corporate social performance in relation to economic performance. If more time periods are available, one has to consider a different modelling strategy, although DEA has alternative specifications that allow dealing with time series data. However, since interest in CSR and sustainable investment increased only recently in the financial markets and in academia, datasets concerning sustainable social and environmental practices, as well as scores assigned to different companies, only span a few years, making it difficult to apply dynamic analysis techniques. Hence, DEA can be very useful in these early stages and is especially useful when only a relative ranking is needed.

One common problem with DEA is that it tends to qualify a considerably large number of units (companies in our case) as perfectly efficient ($\theta^* = 1$). This can pose difficulties if one wants to have a limit on the number of sustainable companies considered for a portfolio. Dyson and Thanassoulis (1988) propose a method to deal with the problem in a single-output framework. One other approach in our particular case could be to choose those companies that along with a $\theta^* = 1$ have good financial results (e.g. stock returns). Another useful approach would be to impose weight restrictions for those inputs (financial measures) that allow this procedure. Recent research shows that feasible solutions can still be found when imposing weight restrictions (Lins *et al.*, 2007).

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Paper II

Strategic Corporate Social Responsibility and Economic Performance

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Abstract

This paper studies the link between Corporate Social Responsibility (CSR) and economic performance of companies. Acknowledging the argument that companies might behave socially responsible strategically, i.e. favoring the CSR dimensions that provide competitive advantages, we construct a novel CSR index based on a Data Envelopment Analysis (DEA) model. We argue that this index accounts for CSR achievements from a strategic perspective, and use it to analyze the link between CSR and economic performance expressed by Return on Assets (ROA). When explicitly accounting for strategic behavior of companies, our findings reveal a significant positive relationship between CSR and economic performance.

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1. Introduction

There has been a continuing interest in what has come to be known as Corporate Social Responsibility (CSR) for at least 50 years. Despite disagreements over an appropriate definition, CSR is generally viewed as corporations' responsibility to integrate environmental, social, and governance (ESG) practices into their business model, beyond mandatory legal requirements. Moreover, CSR is often associated with the notion of sustainable development.

The increased interest in ESG issues has stimulated a rapid development of business and economics literature (Crane *et al.*, 2008) focusing on the relationship between corporate social performance and financial performance (either measured by accounting or market-based measures). However, unequivocal answers are still to be provided. One major difficulty when analyzing the link between CSR and economic performance, as well as one of the reasons for obtaining conflicting results, lies in defining adequate and representative *quantitative* measures for the complex CSR concept.[1]

This paper will address this problem through the construction of a more comprehensive aggregate measure of CSR. Waddock and Graves (1997) expressed the need for a multidimensional measure of CSR applied across a wide range of industries and larger samples of companies. We argue that our constructed CSR index meets these requirements and also accounts for the strategic decisions taken by managers who bear in mind the ultimate goal of profit maximization. Strategic CSR is a concept whose origins can be traced back to Baron (2001), who coined the term to refer to a profit-maximizing corporate strategy that can be regarded as socially responsible by some. Burke and Logsdon (1996) also adopted a view similar to strategic CSR, but focused on the corporate strategy attributes that could be linked to CSR. More recently, Siegel and Vitaliano (2007) performed an empirical investigation concerning the determinants of strategic CSR and also reported evidence of economic benefits derived from strategic CSR. Elsayed and Patton (2005) presented dynamic panel data estimates for the link

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[1] There are a number of additional reasons why it is challenging to find empirical support for the link between economic performance and CSR. For a more detailed exposure, see Waddock and Graves (1997), UNEP Finance Initiative-Mercer Report (2007) and Belu (2009).

between environmental performance and companies' financial performance, arguing that very few studies have controlled for firm heterogeneity or considered dynamic effects in the financial/environmental performance relationship. The present paper addresses this problem by employing a System GMM estimation framework, as in Blundell and Bond (2000).

Porter and Kramer (2006) make a strong case for strategic CSR, arguing that companies should favor a strategic approach to CSR, i.e., they should identify the corporate agenda that can bring the greatest competitive benefit. They claim that "…the more closely tied a social issue is to a company's business, the greater the opportunity to leverage the firm's resources, and benefit society." Moreover, they argue that companies should carefully select the social issues that intersect with their particular business, because: "No business can solve all of society's problems or bear the costs of doing so (...). Other social agendas are best left to those companies (…) that are better positioned to address them."

Recognizing the pertinence of their arguments, we proceed to construct CSR indices that account for the differences between the business models of companies, even within the same industry. In order to achieve this, we resort to Data Envelopment Analysis (DEA), a versatile non-parametric management tool widely used for assessing the relative performance and efficiency of individual decision-making units (DMU) (e.g., firms, schools, hospitals). The DEA feature that we are exploiting most in our study is the assignment of firm-specific sets of weights, with higher weights for outputs where the firm under scrutiny tends to perform better and lower weights for outputs where the firm underperforms, in relative terms. In contrast to this approach, the current practice when constructing CSR indices is to award a subjectively chosen *a priori* set of weights to various CSR dimensions, the same for all companies in a sample or portfolio.

The contributions in the present paper are the following: Firstly, we develop an endogenous CSR index that accounts for *strategic* corporate social behavior. Secondly, we explore the impact of our newly defined measure of CSR performance on return on assets (ROA), which will be modeled as an autoregressive process. We therefore control for past economic performance that might influence both current values for ROA and current CSR. We also control for firm-specific effects that have been shown to affect the

relationship between CSR and ROA (Telle, 2006). Moreover, our empirical model deals to a large extent with concerns of causality in the relationship between CSR performance and ROA, since it includes both unobserved firm-specific effects and past economic performance. We find evidence that strategic CSR impacts ROA positively, when controlling for past economic performance, in addition to a number of other relevant control variables, and industry and firm-specific effects.

The remainder of the paper is organized as follows: Section 2 discusses the heterogeneous nature of the CSR concept and how DEA can be used to construct CSR indices. Section 3 details our empirical strategy. Section 4 presents the data set. Section 5 describes our empirical findings, and Section 6 concludes the paper.

2. The CSR paradigm. Constructing an aggregate CSR measure
2.1 Difficulties with current CSR measures

There is an on-going discussion about the appropriate definition of CSR. However, most of the proposed definitions[2] agree that CSR is a multidimensional concept, which is an aspect of particular concern in this paper. Multi-dimensionality implies that various distinct aspects of the nature of a business need to be considered simultaneously when assessing a firm's CSR performance. These distinct criteria are very often clustered into three main subgroups: environmental, social, and governance related.

The methodologies developed by various CSR rating agencies or data providers[3] involve a subjective weighting of the CSR dimensions' importance. For instance, KLD Research & Analytics, a leading CSR-rating agency, bases its rating criteria on seven qualitative areas: Community, Diversity, Employee Relations, Human Rights (ascribed to the social dimension), Environment, Governance, and Product Safety. Furthermore, they detail the above criteria into *strengths* and *concerns*. Their ratings do not involve numbers, but rather qualitative descriptions noted with pluses and minuses.[4]

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[2] One definition proposed by the European Commission (2001) is as follows: "CSR is a concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with stakeholders on a voluntary basis".
[3] Innovest, IRRC (Investor Responsibility Research Center), Asset4, Sarasin&Cie, KLD Research & Analytics, and Sustainable Asset Management are a few examples.
[4] For details, see the KLD methodology at *http://www.kld.com/research/ratings_indicators.html*

Sustainable Asset Management (SAM)[5] uses a broader list of criteria for assessing CSR performance and updates it every year. For example, in 2007 the following criteria were rated: Corporate Governance, Risk & Crisis Management, Codes of Conduct/Corruption & Bribery, Environmental Performance, Environmental Reporting, Labor Practice Indicators, Human Capital Development, Talent Attraction & Retention, Corporate Citizenship/Philanthropy, and Social Reporting.

SAM computes a score from 0 to 100 for each dimension, where a score of 100 means maximum performance. The assessment of the score is done by in-house specialists either based on questionnaires completed by companies or on publicly available sources of information. In the present study we will use the individual scores provided by SAM to construct our proposed CSR index.

One can notice from the criteria listed above that a wide range of issues are addressed simultaneously in an assessment of a firm's social responsibility. However, there might be differences in the way these issues affect different businesses. Some dimensions are certainly important for some businesses, while others are less relevant. For instance, oil and mining companies are very exposed to environmental risks and therefore deploy strategies with respect to environmental performance accordingly; banks and financial institution put a higher emphasis on risk and crisis management, while IT companies have extensive human capital development strategies and consequently are expected to score high in terms of labor practices. We assume that managers carefully select the CSR issues that are deemed relevant for their company and then concentrate their efforts in those particular areas.

Although a number of authors (Bagnoli and Watts, 2003; Besely and Gatak, 2007) view CSR as a public good that is provided privately, one can see from the above listed dimensions, commonly considered when assessing CSR, that some issues like human capital development and risk and crisis management do not have the characteristics of a public good. We favor the view of *strategic* CSR as in Baron (2001), Porter and Kramer (2006) or Heslin and Ochoa (2008).

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[5] Sustainable Asset Management is a Swiss based asset management company that computes and updates Dow Jones Sustainability Index. In addition to general CSR criteria, SAM also computes sector-specific criteria. See *http://www.sam-group.com/* for details.

Different CSR dimensions imply different costs and might provide different benefits and opportunities for profit, depending on the nature of the firm's core business. Thus, it is difficult to construct an aggregate measure of CSR in a fair manner, even if accurate information about the achievements in terms of each particular dimension is available. One has to decide on a set of weights to be used for computing an aggregate index. Depending on the structure of the weighting system, more emphasis might be placed on some dimensions and less on others. This subjective way of computing CSR indexes is prone to criticism, as it might favor some dimensions over others and therefore some companies over others.

Another research strategy is to conduct separate analyses for each CSR component, i.e., to analyze the causality between a measure of economic performance and one particular CSR component (e.g., corporate governance, environmental performance, or labor practices). While many authors have chosen this route (Manescu and Starica, 2007; Hart and Ahuja, 1996; King and Lenox, 2001), the potential findings are not really useful in our context since even if a negative relationship is found for an individual CSR component, we do not want that particular CSR component to be discarded from an aggregate measure of CSR altogether. On the other hand, if positive relationships are found, it is difficult to argue that the result can be generalized for companies with significantly different businesses, and it is also unclear how much of its available resources a company should commit to that particular CSR dimension, perhaps to the detriment of other relevant CSR dimensions.

In addition to the above arguments, Baron (2001) argues that in the presence of opportunities for strategic CSR, a positive correlation between economic performance and CSR should be expected. However, when altruism rather than profit maximization drives CSR, a negative relationship might also be possible. Consequently, the empirical analyst should know beforehand whether displayed CSR is a result of altruism, profit maximization, or a threat by an activist. Our approach avoids such burdensome information requirements, since this information is implicitly embedded in our constructed CSR indices based on DEA.

2.2 How can DEA be used to construct endogenous CSR indexes?

The following brief presentation of the DEA method is based mainly on Cooper *et al.* (2000). The standard DEA models account for production-like processes, where multiple inputs are combined and transformed into several outputs. The main purpose of DEA is to construct an index (score) of relative (to the other units) performance. To obtain this, the first step is to construct a virtual input and a virtual output for each DMU by using a set of (unknown ex ante) weights:

$$Virtual\ input = v_1 x_{1o} + ... + v_m x_{mo}$$

$$Virtual\ output = u_1 y_{1o} + ... + u_s y_{so},$$

where *v* and *u* are weights and *x* and *y* are inputs and outputs, respectively.

The next step is to determine the weights, using linear programming techniques, so as to maximize the ratio:

$$\theta = \frac{v_1 x_{1o} + ... + v_m x_{mo}}{u_1 y_{1o} + ... + u_s y_{so}}. \tag{1}$$

Consequently, the optimal weights may vary from one DMU to another. Hence, deriving the optimal weights from data is an objective process, compared to fixing them in advance. It is important to realize that there is a ratio for each DMU, so we will get N maximal values (θ^*) and an optimal set of weights for each unit in the sample. The ratio θ^* is restricted to be less than or equal to 1, and the units that have a $\theta^* = 1$ after optimization are considered to be efficient, i.e., performing best. The lower the calculated θ^*, the more inefficient the unit. This ratio will constitute the base for the CSR index that will be used as an explanatory variable in the empirical model.

DEA constructs the weights endogenously by allowing them to be determined as part of an optimal solution to a formal aggregation problem. More precisely, DEA assigns higher weights to dimensions where a company performs well and lower weights to dimensions where it performs less well. The weights will be chosen such that each company will be placed in the most favorable position in relation to all other companies in the sample. In this manner, we can obtain a score for the relative performance in terms of CSR, for each particular company. The optimal set of weights is determined as part of

an optimization process and is company specific. In other words, the DEA weighting system favors dimensions where the company performs better, corresponding to the business strategy implemented by its manager. This means that CSR dimensions that provide competitive advantages and implicitly receive increased ex ante efforts from the manager, as reflected in correspondingly higher SAM marks, will weigh heavier in the aggregate CSR index.

Moreover, DEA provides the means to identify in which dimension a particular firm is lagging behind best practice in CSR terms. It can also provide precise quantitative qualifications to the sub-optimal level for a firm; hence it gives the percentage by which a particular sub-optimal firm should improve in a certain dimension in order to achieve best practice.

For our empirical analysis, we construct a DEA index that considers all CSR dimensions as outputs. No particular quantity is considered as an input. We will base our approach on the model developed by Lovell and Pastor (1997), where only one constant input is considered. The reason for this is that we consider each firm as a stand-alone unit, without explicitly accounting for various inputs involved in obtaining the current environmental, social, or governance-related accomplishments. While it is obvious that achieving a satisfactory CSR level might require material inputs, usually it is not clear how these are converted into CSR scores. What we aim to measure is the commitment of a particular firm to the CSR requirements.

Moreover, the separation into CSR-efficient and CSR-inefficient firms is performed at the industry level in order to reduce inter-industry heterogeneity, although a CSR index could be meaningfully computed industry-wide. Therefore, as the level of inefficiency is industry specific, we will only distinguish between efficient and inefficient firms. We will construct a dummy variable for this purpose, which will take the value 1 for efficient units and 0 for inefficient units, regardless of the exact degree of inefficiency.

If we let $y_j = (y^{1j}, y^{1j} ... y^{7j})$ represent the vector of CSR scores (provided by Sustainable Asset Management) for the firm j, $j=1...N$ where N is the number of firms in the sample, then we can write the following optimization problem:

$$\max_{\theta,\lambda} \theta y^{ij}$$

subject to

$$\theta y^{ij} \leq \sum_k \lambda_k y^{ik}, i = 1,..,7$$

$$\lambda_k \geq 0, k = 1,...j...,N$$

$$\sum_k \lambda_k = 1$$

(2)

where i indexes the CSR dimension, k indexes the firms under scrutiny, and λ_k are the assigned weights for each dimension. This model was proposed and used in Lovell and Pastor (1997) to analyze the operating performance of branch offices of a large financial institution in the context of target setting. In our case, we do not have any target requirements, although this procedure can be implemented by the screening agent in a fairly easy manner, as shown in the paper mentioned above.

DEA models are devised *input-oriented* or *output-oriented*. The distinction comes from the way adjustments are made to inefficient units in order to obtain their efficient projections. If adjustments are made in the input space, we have the *input-oriented* approach. If adjustments are made in the output space, we have *output-oriented* models. There is also a third choice, namely models that simultaneously adjust both outputs and inputs, the so-called *additive* models with their *slack-based* variants. However, in our case, the distinction is less relevant. As a matter of convenience, we will choose the output-oriented model, like in Banker et al. (1984). Given that there is only one input, the nature of returns to scale is not important either. Lovell and Pastor (1999) showed that an output-oriented model (which assumes constant returns to scale, like in Charnes et al. (1978)) with a single constant input, coincides with the Banker et al. (1984) model (which allows for variable returns to scale) with a single input.

3. Empirical strategy

Our empirical exercise is concerned with investigating whether *strategic* CSR behavior is a determinant of economic performance. As a proxy for economic performance we will use return on assets (ROA_{it}), a profitability measure that expresses the amount of net earnings after interest payments and taxes per unit of assets. Our

measure of socially responsible behavior is the CSR index whose construction was described in Section 2.2.

Following previous studies (e.g., Manescu and Starica, 2007), we consider a number of additional control variables to explain firm profitability, in addition to the CSR factor. These variables are: firm size *(Size)*, measured as the natural logarithm of assets expressed in US dollars; leverage *(Lev)*, expressed as long-term debt/assets; capital intensity (*Cap_int*), calculated as the ratio of capital expenditures to fixed assets; retained earnings *(Ret_E)* as a proxy for R&D expenses;[6] firm growth (*dSales*), expressed as a 3-year percentage change in sales (King and Lenox, 2001); price-to-book ratio *(PToB)* (Fama, French 2000); and dividends-to-book ratio *(Div_B)* (Miller and Modigliani, 1961). We control for industry effects (*DInd*) and include our computed CSR scores among the explanatory variables. Under these assumptions, the model to be estimated for the pooled sample is:

$$ROA_{it} = \alpha + \beta_1 CSR_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 PToB_{it} + \beta_5 \operatorname{Re} t\_E_{it} +$$

$$\beta_6 Cap\_i\operatorname{nt}_{it} + \beta_7 dSales_{it} + \sum_{j=1}^{4} \gamma_j DY_j + \sum_{k=1}^{9} \delta_k DInd_k + (u_i + \varepsilon_{it})$$

(3)

DY_j represents year dummies controlling for year-specific effects; ε_{it} is distributed as $N(0,\sigma^2)$.

Moreover, as our sample covers firms that differ in terms of, e.g., accounting reporting principles, productivity, and management competence in the form of unobserved firm heterogeneity, we need to include time invariant firm specific effects, i.e., u_i, in the empirical model.

Along the lines of Fama and French (2000) who model ROA as a mean-reverting process, we use a dynamic model for return on assets where current values of ROA are linked to past values of ROA. Thus, ROA is modeled as an autoregressive of order 1 (AR(1)) process following, e.g., Sigel and Vitaliano (2007) and Elsayed and Paton (2005).

When estimating a dynamic panel data model, the lagged dependent variable (as an explanatory variable) is correlated with the fixed-effects term entering the compound

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[6] Firm-level values for R&D expenses are rarely available in Datastream.

disturbance, and this requires some additional steps in the estimating procedure. The general approach relies on instrumental variable (IV) estimators. The initial solution to the endogeneity problem in the presence of firm-specific effects was proposed by Anderson and Hsiao (1981) and consists of estimating equation (4) in first differences and using the second lag of ROA_{it} as an instrument, provided that the ε_{it} components of the errors are uncorrelated. However, if the data allows several instruments that are available for the first-differenced equations in later time periods, then efficiency can be improved. The reasons are that: (i) more instruments generate efficiency gains and that (ii) in the presence of overidentifying restrictions one could use an optimal weight matrix in a Generalized Method of Moments (GMM) framework. Arellano and Bond (1991) have developed the framework for the "Difference GMM" estimator, which makes use of the maximum number of lags of the endogenous variable as instruments, at each point in time. However, Blundell and Bond (2000) report that the Difference GMM estimator could produce both downward biased as well as very imprecise estimates in the presence of weak instruments and a high autocorrelation coefficient. For this reason, they propose the System GMM estimator, which brings improvements both in terms of bias reduction and efficiency gains. Besides the equations in differences as in the Difference GMM estimator, the System GMM estimator also includes equations in levels for which the appropriate differences in lags of the endogenous variable are used as instruments. An additional assumption made in System GMM is that first differences of instrument variables are uncorrelated with fixed effects. This allows the introduction of more instruments that can dramatically improve efficiency. The model to be estimated with System GMM is thus:

$$ROA_{it} = \alpha + \beta_0 ROA_{it-1} + \beta_1 CSR_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 PToB_{it} + \beta_5 \operatorname{Re}t\_E_{it} +$$
$$\beta_6 Cap\_\operatorname{int}_{it} + \beta_7 dSales_{it} + \sum_{j=1}^{4} \gamma_j DY_j + \sum_{k=1}^{9} \delta_k DInd_k + (u_i + \varepsilon_{it}) \tag{4}$$
.

      In a subsequent step, we use the same specification but with lagged values for CSR. The reason for this is that CSR measures might translate into the next period's

economic results. One might also suspect correlation between current values of the control variables and the CSR scores.

4. Data

Our data set consists of an average annual sample of 372 non-financial large publicly traded companies listed on the main international stock exchanges, leading to around 1860 firm-year observations from 2002 to 2006. The sample covers nine industries defined according to the MSCI global industry classification standards (GICS): Oil and Gas (10.2%), Industrials (23.8%), Consumer Goods (16.9%), Healthcare (6.5%), Consumer Services (13.6%), Telecommunications (4.4%), Utilities (9.9%), Technology (8%), and Basic Materials (6.7%). We excluded Financials as they are oddly regulated, which may produce unusual behavior of profitability (Fama and French, 2000). The regional distribution of the sample covers 45% European, 30% North-American, and 15% Japanese companies.

As mentioned, the dependent variable is Return on Assets (ROA).[7] The explanatory variable of interest is the CSR aggregate index as defined in Section 2.2. This yearly index is constructed based on seven selected CSR dimensions that were rated every year of the analyzed period. These CSR dimensions are: Codes of Conduct/Bribery & Corruption, Corporate Citizenship, Corporate Governance, Eco-Efficiency, Human Capital, Risk Management, and Talent Attraction.

The other control variables, described in Section 3, were obtained from Worldscope Datastream. Moreover, eight industry dummies were also included among the explanatory variables, as well as lagged values of the ROA variable. Summary statistics of the data set are provided in Table 1 below:

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[7] See the Annex for additional data details.

Table 1. Summary Statistics of the variables in the data set: firm size (Size), leverage (Lev), price to book ratio (PToB), dividend to book ratio (DToB), retained earnings (Ret_E), 3-year percentage change in sales (Dsales), and capital intensity (Cap_Int).

Variable		Obs	Mean	Std. Dev.	Min	Max
ROA_{it}		1871	6.631694	5.953947	-22.31	53.95
ROA_{it-1}		1861	5.995019	6.127134	-56.65	45.18
CSR		1871	.4409407	.4966325	0	1
Size		1871	16.31283	1.269335	11.29	20.44
Lev		1871	19.99801	13.15943	0	85.37
PToB		1871	3.354805	5.9282	.3	134.52
DToB		1871	7.417852	15.15229	0	331.36
Ret_E		1871	17.72725	18.49948	0	129.50
Dsales		1871	7.614848	13.0617	-47.67	139.41
Cap_Int		1871	19.22604	12.33776	0	131.25

5. Empirical results

Multi-collinearity among the explanatory variables in Model 1 is not an issue in our sample except for the dividend-to-book and price-to-book ratios. The pairwise correlation coefficient matrix in Table 2 reveals that while most coefficients lie between the reasonable values of -.26 (capital intensity and leverage) and .23 (price-to-book and lagged ROA), the correlation coefficient between price-to-book and dividend-to-book is .83 (statistically significant at the 1% level). For this reason as well as due to higher variation in the price-to-book variable, we have decided to drop the dividend-to-book ratio from the list of explanatory variables.

Table 2. Correlation coefficients of the explanatory variables in Model (1).

	ROA_{it}	PToB	DToB	Lev	Ret_E	Dsales	Cap_int	Size
ROA_{it}	1.0000							
PToB	0.2307*	1.0000						
DToB	0.2042*	**0.8245***	1.0000					
Lev	-0.1719*	0.0391	0.1378*	1.0000				
Ret_E	0.2069*	0.0738*	0.0158	-0.3293*	1.0000			
Dsales	0.1925*	0.0307	0.0118	-0.0277	-0.0882*	1.0000		
Cap_int	0.1215*	0.0693*	-0.0279	-0.2593*	-0.0031	0.1344*	1.0000	
Size	-0.1630*	-0.1256*	-0.0626*	0.1627*	-0.1208*	-0.1310*	-0.0806*	1.0000
CSR	**0.0451**	**-0.0062**	**-0.0063**	**-0.0290**	**0.0631***	**-0.0145**	**-0.0407**	**0.2061***

* significant at the 1% level.

As a preliminary step, we have estimated Model (1) for each of the five years 2002-2006 (see Table 3) as well as for the pooled sample. The dependent variable ROA is modeled as a function of the CSR index and several control variables, including industry dummies. Without controlling for past economic performance, our model has a reasonable explanatory power ranging from .21 to .33, which is in line with previous findings (Fama and French, 2000, p.166). Moreover, the CSR index is found to be positively related to ROA every year. Compared to a CSR inefficient firm (i.e., CSR=0), the marginal effect of the CSR index on ROA is .59% to 1.83 % higher for a CSR efficient firm (i.e., CSR=1). In the pooled sample, the average marginal effect for CSR efficiency is positive (i.e., 1.17) and statistically significant at the 1% level. The increasing magnitude of the intercept in the estimated models from 2002 to 2006 is partly due to a nearly two-fold increase in yearly average ROA (from 4.73 in 2002 to 8.42 in 2006).

Table 3. Yearly regression and pooled OLS estimates for Model (1):

VARIABLES	2002	2003	2004	2005	2006	Pooled OLS[#]
CSR	1.28**	0.74	1.06**	0.59	1.83***	1.17***
	(0.04)	(0.14)	(0.03)	(0.33)	(0.00)	(0.00)
Size	-0.57***	-0.33	-0.56***	-0.81***	-1.08***	-0.67***
	(0.01)	(0.11)	(0.01)	(0.00)	(0.00)	(0.00)
Leverage	-0.03	-0.03	-0.04*	-0.02	-0.10***	-0.04***
	(0.29)	(0.17)	(0.06)	(0.38)	(0.00)	(0.00)
PToB	0.20***	0.68***	0.15***	0.21***	0.38***	0.24***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ret_E	0.05**	0.05***	0.08***	0.10***	-0.07***	0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dsales	0.08***	0.00	0.05***	0.07***	0.04	0.04**
	(0.00)	(0.76)	(0.01)	(0.01)	(0.12)	(0.02)
Cap_int	-0.02	0.04	0.04*	0.06**	0.07***	0.04**
	(0.40)	(0.10)	(0.07)	(0.02)	(0.00)	(0.01)
Constant	10.94***	9.60***	14.95***	19.95***	27.83***	15.46***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Year Dummy	-	-	-	-	-	Y
Industry Dummy	Y	Y	Y	Y	Y	Y
Observations	343	360	395	391	382	1871
Adj. R-squared	0.21	0.30	0.27	0.26	0.33	0.27

P-values in parentheses; [#]Robust p-values in parentheses; ***p<0.01, **p<0.05, *p<0.1.

However, given the autoregressive nature of the ROA process, it is expected that the estimated coefficients of all explanatory variables in a model without lagged ROA are biased due to the omitted variable. This fact is confirmed when re-estimating the model for ROA (with OLS) but including lagged ROA, i.e., Model (2) (see Table 4). First, the coefficient estimate for the lagged ROA variable is consistently positive, ranging from .36 to .77, and statistically significant at the restrictive 1% level in all year regressions. This fact, corroborated with the two-fold boost in the adjusted R-sq relative to that of previous models, confirms the necessity of including lagged ROA in the model for ROA. Also, the coefficient estimate for lagged ROA in the pooled OLS model (.54) is very close in magnitude to the corresponding estimate (.57) in Fama and French (2000) (see Table 4, Col 6). Second, it can be noticed that while the impact of the CSR index is still positive and statistically significant in the pooled model, it drops in magnitude by almost

a half (.81 versus 1.17). This constitutes evidence that the impact of CSR performance on economic performance to a certain extent is determined by past economic performance (King and Lenox, 2001).

Table 4. Yearly regression and pooled OLS estimates for Model (2).

VARIABLES	(1) (2002) Roa	(2) (2003) roa	(3) (2004) roa	(4) (2005) Roa	(5) (2006) roa	(6) (P-OLS) [#] roa
CSR	0.99*	0.91**	0.88**	0.48	0.50	0.81***
	(0.06)	(0.03)	(0.03)	(0.31)	(0.27)	(0.00)
ROA_{it-1}	0.51***	0.36***	0.57***	0.77***	0.69***	0.54***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size	-0.20	-0.16	-0.49***	-0.14	-0.50**	-0.33***
	(0.27)	(0.35)	(0.00)	(0.49)	(0.01)	(0.00)
Lev	-0.02	-0.03	-0.03	-0.00	-0.06***	-0.03***
	(0.29)	(0.16)	(0.14)	(0.82)	(0.00)	(0.00)
PToB	0.16***	0.44***	0.07***	0.07	0.15***	0.14***
	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
Ret_E	-0.01	0.04***	0.02*	0.01	-0.05***	0.01
	(0.74)	(0.00)	(0.07)	(0.40)	(0.00)	(0.23)
Dsales	0.03*	-0.01	-0.00	0.02	-0.02	0.01
	(0.09)	(0.43)	(0.98)	(0.34)	(0.21)	(0.63)
Cap_int	-0.02	0.04	0.04*	0.00	0.04**	0.02*
	(0.26)	(0.11)	(0.06)	(0.86)	(0.02)	(0.05)
Constant	2.96	5.91*	11.40***	5.29	12.43***	7.55***
	(0.36)	(0.05)	(0.00)	(0.14)	(0.00)	(0.00)
Industry D	Y	Y	Y	Y	Y	Y
Year D	Y	Y	Y	Y	Y	Y
Observations	343	358	395	383	382	1861
R-squared	0.43	0.49	0.48	0.55	0.58	0.50

P-values in parentheses; [#]Robust p-values in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Despite improvements, coefficient estimates in model (2) are still subject to bias and inefficiency due to the presence of firm-specific effects (u_i) that are correlated with the explanatory variable lagged ROA. Therefore, the next estimation steps are undertaken to solve the endogeneity problem of lagged ROA, which otherwise generates bias in all coefficient estimates. For this reason, it is likely that the actual coefficient estimate of lagged ROA lies between the OLS estimate, which is upward biased, and the within-

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groups estimate, which is expected to be downward biased (Blundell and Bond, 2000) due to the rather limited time horizon T (i.e., 5 years). The pooled OLS and within-group estimation results of Model (2) displayed in Table 5 indicate that the true autoregressive coefficient on lagged ROA lies between .04 and .54.

Using either ROA_{it-2} as the sole instrument (i.e., Table 5, Col. 3) or all instruments dated t-2 (i.e., Table 5, Col. 4) in the estimation of Model 2 in first-differences produces only minor improvements in the estimated coefficient on lagged ROA. This autoregressive parameter is still downward biased toward the within-group estimate (.11 and .09, respectively). At the same time, the validity of the instruments is confirmed both by accepting the null hypothesis of no second-order autocorrelation in the first differenced residuals for the Anderson and Hsiao (1981) model and by the Hansen test, which does not seem to reject the validity of the nine overidentifying restrictions in the Diff GMM estimation. We have implemented the one-step GMM estimator since it has been found to be more reliable than the (asymptotically) more efficient two-step estimators (Blundell and Bond, 2000).

As the estimate of the ROA autoregressive parameter β_0 is not statistically significant when using the limited number of instruments available for the Diff GMM estimation, we go one step further and implement the System GMM estimator, thus making use of all available information in the data. Column 5 in Table 5 displays a reassuring estimate for $\beta_0 = .27$, which apparently is higher than the within-estimate and well below the OLS estimate. Moreover, the Hansen test of the overall overidentifying restrictions cannot be rejected at the 8% level, though the additional three restrictions (in differences) are only marginally valid (the corresponding Hansen test can be rejected at the 1% level).

Table 5. Pooled OLS (Col. 1), Within-Group (Col. 2), Difference Equations instrumented (Col. 3), Difference GMM (Col. 4) and System GMM (Col. 5) estimation of Model (2):

VARIABLES	(1) OLS Levels	(2) Within Groups	(3) Diff IV	(4) DIFF GMM	(5) SYS GMM
ROA_{it-1}	0.54***	0.04	0.11**	0.09	0.27***
	(0.00)	(0.11)	(0.02)	(0.15)	(0.00)
CSR	0.81***	0.09	0.07	0.03	0.63**
	(0.00)	(0.73)	(0.77)	(0.90)	(0.01)
Size	-0.33***	-3.13***	-3.87***	-3.99**	-0.55***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Lev	-0.03***	-0.09***	-0.07***	-0.08*	-0.05***
	(0.00)	(0.00)	(0.01)	(0.09)	(0.00)
PToB	0.14***	0.06*	0.00	0.00	0.16***
	(0.00)	(0.06)	(0.89)	(0.94)	(0.00)
Ret_E	0.01*	-0.04***	-0.05***	-0.05***	0.01
	(0.09)	(0.00)	(0.00)	(0.00)	(0.42)
Dsales	0.01	0.03**	0.02	0.02	0.01
	(0.50)	(0.02)	(0.29)	(0.24)	(0.25)
Cap_int	0.02***	0.06***	0.03**	0.03**	0.03**
	(0.01)	(0.00)	(0.02)	(0.05)	(0.03)
Constant	7.55***	59.35***	0.87***		16.92***
	(0.00)	(0.00)	(0.00)		(0.00)
Year, Industry D	Y,Y	Y,Y	Y,Y	Y,Y	Y,Y
m2			0.66	0.76	0.33
m3			0.69	0.71	0.83
Hansen				0.104	0.082
Diff. in Hansen				-	0.005
# Overid. Restrictions	-	-	0	9	13
Observations	1861	1861	1229	1229	1861
R-squared	0.50	0.16	-	-	-
Number of isinID		596	428	428	596

p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1; m2 and m3 are tests for second-order and third-order serial correlation in the first-differenced residuals, asymptotically N(0,1). Hansen is a test of over-identifying restrictions for the GMM estimators. Diff. in Hansen is a test of *additional* moment conditions used in the System GMM estimators relative to the corresponding first-differenced GMM estimators. P-values are reported for all tests.

In order to gain additional support for the system GMM estimator and following the Blundell and Bond (2000) strategy, we estimated a simple AR (1) specification of the ROA model with the four alternative methods (see Table 6). Despite the fact that lag ROA at time *t*-2 and earlier are valid instruments according to the Hansen test (Col 3),

the estimated autoregressive parameter $\beta_0 = .16$ seems to still be biased toward the within-group estimate. On the contrary, the system GMM estimator provides a more reasonable estimate of .31 and all overidentifying restrictions are valid (p-value Hansen test =.20) (Col 4). We will therefore rely on the estimates of the system GMM estimator for our Model 2.

Table 6. Pooled OLS (Col. 1), Within-Group (Col. 2), Difference GMM (Col. 3) and System GMM (Col. 4) estimation of the AR (1) model for ROA:

$$ROA_{it} = \alpha + \beta_0 ROA_{it-1} + \sum_{j=1}^{4} \gamma_j DY_j + \sum_{k=1}^{9} \delta_k DInd_k + (u_i + \varepsilon_{it})$$

$$(5)$$

VARIABLES	(1) OLS Levels	(2) Within Groups	(3) Diff GMM	(4) SYS GMM
ROA_{it-1}	0.61***	0.06**	0.16**	0.31***
	(0.00)	(0.02)	(0.01)	(0.00)
Constant	2.51***	7.75***		8.32***
	(0.00)	(0.00)		(0.00)
Year, Industry D	Y,Y	Y,Y	Y,Y	Y,Y
m1			0.69	0.37
m2			0.79	0.77
Hansen			0.418	0.198
Diff. Hansen			-	0.026
# Overid. Restrictions	-	-	9	13
Observations	1861	1861	1229	1861
R-squared	0.46	0.10		
Number of isinID	596	596	428	596

p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1; m2 and m3 are tests for second-order and third-order serial correlation in the first-differenced residuals, asymptotically N(0,1). Hansen is a test of over-identifying restrictions for the GMM estimators. Diff. Hansen is a test of *additional* moment conditions used in the System GMM estimators relative to the corresponding first-differenced GMM estimators. P-values are reported for all tests.

In the System GMM estimation (Table 5, Col. 5), the marginal effect of being a CSR efficient unit versus a CSR-inefficient unit implies an economically significant .63% higher ROA, independent of industry classification and the other controls. Thus, we have found evidence that the firms that undertake the CSR activities mostly suitable to their business model, i.e., strategic CSR, are more profitable.

Our results are related to several lines of empirical findings on the link between CSR performance and economic performance. First, not only do we investigate the impact of environmental performance on profitability measures as most studies in this area (Russo and Fouts, 1997; Waddock and Graves, 1997; Hart and Ahuja, 1996), we also account for other CSR dimensions as a few other studies do (e.g., Manescu and Starica, 2007). Second, while we do provide evidence of a positive and economically significant impact of CSR performance on profitability (as measured by return on assets), we also to a large extent solve the causality concern by controlling for past economic performance, and use proxies for research and development expenses (i.e., retained earnings) that have been shown to impact both CSR and ROA. Third, but not least, we have shown that it is *strategic* CSR that positively impacts profitability.

It is also worth noting that the model we estimate behaves well in the sense that the effects of the control variables have the sign predicted by the established theory.

6. Conclusions

In empirical investigations where a quantitative measure of corporate social responsibility is required, one of the main difficulties is to account for the multidimensional and heterogeneous nature of the concept. It is difficult to aggregate company achievements with respect to various CSR dimensions in a way that leads to a fair and meaningful index.

This paper proposes a novel method based on DEA, a mathematical model traditionally used for efficiency analyses, to aggregate various CSR dimensions while considering the notion of strategic CSR, as emphasized in Baron (2001) and argued for in Porter and Kramer (2006). We assume that managers correctly identify and favor the dimensions of CSR that might provide their companies with competitive advantages, and our constructed CSR index accounts for this strategic CSR behavior.

Based on a set of dimension-specific CSR scores provided by a specialized screening agency, we construct the aggregate CSR index described above and employ a SYS-GMM estimation technique to analyze the relationship between strategic CSR and

economic performance in a dynamic framework, using a 5-year panel of 372 non-financial publicly traded large corporations.

We find a persistently positive link between strategic CSR and the economic performance of companies. This implies that there is potential for increased profitability when conducting business with consideration to the competitive advantages provided by CSR.

The novel use of DEA to construct the CSR index allows for performing empirical analyses centered on strategic CSR and opens the path for in-depth studies of the competitive benefits provided by various CSR dimensions.

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ANNEX

Data description

Compilation of CSR data is usually a tedious process. For example, CSR performance in year *t* is reflected in the CSR scores published in September year *t+1*. We therefore need to ensure that both the dependent variable (i.e., return on assets) and the explanatory variables (i.e., CSR variable and controls) are *contemporaneous*. As the ends of the fiscal years of the firms in our samples range from January to December, we have designed a representative matching rule according to which there is at least a six months overlap between the period reflected by the CSR measure and the financial data. Thus, CSR data for year *t* (which in fact reflects CSR performance in year *t*-1) is linked to financial data for either January-May in year *t* or for June-December in year *t*-1, depending on the firms' fiscal year ends.

Paper III

The effect of IT capital on the efficiency of Swedish banks

Constantin Belu[a]

Abstract:

This paper investigates the impact of Information Technology (IT) capital on the technical efficiency of Swedish banks against the background of the so-called "productivity paradox," which puzzled economists in the 1990s. Panel data of 85 banks observed during 1999-2003 is used for this purpose. Employing a stochastic frontier production function that allows for time-varying technical efficiencies shows that the technical efficiency of Swedish banks increased with the amount of employed IT capital.

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'You can see the computer age everywhere but in the productivity statistics',
Robert Solow, 1987

1. Introduction

There is a widespread belief that Information Technology (IT) boosts economic growth and productivity. Nonetheless, this effect has been surprisingly difficult to detect. Even in the US, the world's leader in both production and consumption of IT, a significant productivity increase was not noticed until the mid-1990s, although IT investment had been strong since the mid-70s. This phenomenon has been referred to as the 'productivity paradox',[1] and statements like 'No, computers do not boost productivity, at least not most of the time' (The Economist, 1990) have been made, which is in great contrast to the enormous expectations of the information age. Of course, this paradox has stimulated research, both at the macro and micro level. It seems that Solow's remark was valid until late1990s but not afterwards.

At the macro level, in the growth accounting framework, Jorgenson (2001) in his Presidential Address to the American Economic Association, demonstrated that the "relentless decline in the prices of information technology" is the key to understanding the quite amazing growth resurgence in the US economy after 1995.The IT price decline is the critical component of the cost of capital in assessing the powerful impact of the resulting IT investment on economic growth. Massive substitutions of IT inputs for other types of capital and labour services are explained by the remarkable decline in IT prices. Computers dominate the growth impact, but communications equipment and software have made important contributions as well. Together these components boosted US economy growth by about half a percent between 1995 and 1999. The Presidential Address was further developed, in a major effort to quantify the impact of information technology on the US economy, in Jorgenson et al. (2005) and (2007).

At the micro, firm level, results appear to be more mixed, but still relatively little is known about the impact of IT technology in different activities; see Huang (2005) for some references. According to Wolf (1999), in the US, finance, insurance

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[1] A comprehensive review of the 'productivity paradox' and the related literature is available in Brynjolfsson (1993). A later review and assessment of the paradox is Triplett (1999).

and real estate had the highest IT investment in terms of full-time equivalent employee during the period 1958-1987. In Sweden, in recent years, retail banking has benefited tremendously from the support of IT, and Internet Banking has experienced a significant increase (see Fig. 1). An important question in this context is whether this new way of conducting banking business has led to an improvement in the efficiency of banks. Many commentators believe that the answer is affirmative and that the improvement is in fact so dramatic, it is likely to change the way the business will be managed in the future (Llewellyn, 1999). Internet banking is today among the basic offers of any serious retail bank, but since there seem to be very few studies of the impact on bank performance of IT technology, rigorously assessing the contribution of IT capital to the overall performance of a bank is still a relevant problem.

Figure 1. No. of internet customers of Swedish banks at the end of each year
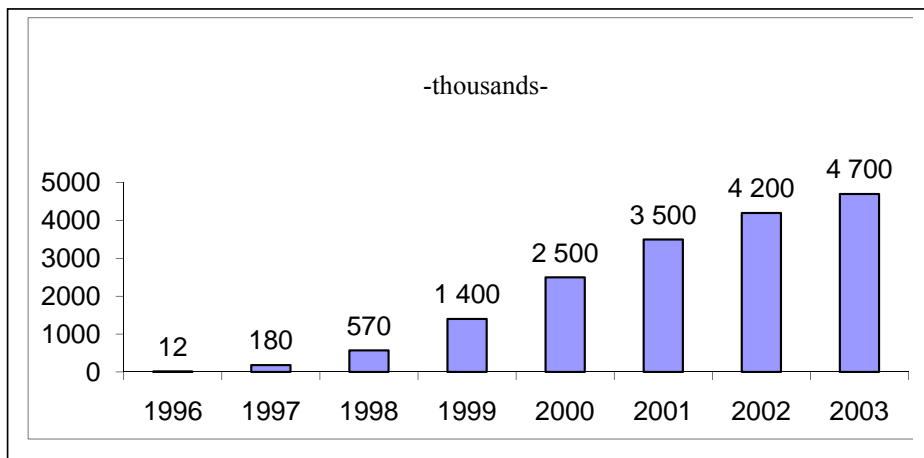
Source: Swedish Banker's Association.

The question of what factors determine productivity growth is central in production theory. The literature suggests e.g. managerial skills, human capital, R&D expenditure and ICT investment; however, researchers have not quite agreed on the specification of an appropriate model for assessing the impact of these factors on firm productivity. Studies looking at the factors that affect productivity may be affected by methodological or econometrical problems that can induce serious estimation biases.

The aim of this paper is to provide answers to the following questions: Has the intensive use of IT capital had a significant impact on Swedish banks' efficiency?

And, if the answer is affirmative, what are the direction and magnitude of this effect? Since we are concerned with evaluating the exogenous effect of one factor on productivity, our modelling strategy will be based on the stochastic production frontier, a tool that has been extensively developed in recent years; see Greene (2004) for a review.

The remainder of the paper is organised as follows. The next section describes the econometric model(s) used and provides a brief review of the related literature. Section 3 describes the data used. Section 4 presents and discusses the estimation results and Section 5 summarises the paper and sets forth some conclusions.

2. The econometric specification

As already mentioned in the introduction, our aim is to investigate whether IT has had an impact on the efficiency of Swedish banks. As a proxy for IT capital, we will use the actual level of expenditure (*IT expenditure*) of each bank for IT related items. The reason why this is an appropriate proxy will be discussed later.

When we refer to *IT expenditure* as exercising an exogenous influence on productivity, we want to express the influence that the choice of *IT expenditure* might exert on bank productivity, but not endogenously, like the choice of regular inputs (e.g. labour or capital). In a way, *IT expenditure* is seen as a 'background' or an environmental variable, but with a direct and significant impact on the productivity of each specific bank. Also, recall that *IT expenditure* is in fact a proxy for IT capital, which is ultimately our variable of interest. For estimation purposes we have to assume that the choice of *IT expenditure* is made by banks independently of their observed productivity. This assumption is not very restrictive in reality, if we accept that there might be a variety of reasons not related to productivity why banks would want to employ more IT capital (e.g. keeping up with the latest technology, increasing market share, scale economies etc.). Hancock et al. (1999) discuss the trade-off between economies of scale and IT expenditure related to the consolidation of bank-braches in the US.

It is important to distinguish between productivity change and technical efficiency. In a scalar output case, productivity change (also called the Solow residual or the Divisia index of productivity change) is defined as the difference between the rate of change of the output and the rate of change of an input quantity index.

Productivity change can be decomposed into several components: changes attributed to pure technical change (improvements over time in the underlying technology), a scale effect, an allocative effect and a technical efficiency change (Kumbhakar and Lovell, 2000).

The allocative effect can be disentangled only if information about input prices is available. Since we do not have such information for the present study, we have to assume allocative efficiency.

Using panel data for the Swedish banking industry, this paper investigates the effect of *IT expenditure* on the *technical efficiency* of Swedish banks. We will resort to a stochastic production frontier model, with a development as in Battese and Coelli (1995). Similar approaches were used in Kumbhakar *et al.* (1991), Reifschneider and Stevenson (1991) and Huang and Liu (1992). For a review on the subject, see Simar *et al.* (1994). Forsund and Hjalmarsson (1979) was an early proposal for panel data estimates of a production function, although the approach is not parametric.

As mentioned earlier, *IT expenditure* will be regarded as having an exogenous effect on bank performance. One shortcoming of the classical stochastic production frontier analysis is that although it identifies technical inefficiencies for individual units, it does not explicitly formulate a model for identifying the causes of these inefficiencies or the factors that influence the production process in a way that leads to inefficiency. There have been some attempts to deal with this issue. Pitt and Lee (1981) and Kalirajan (1981) adopted the so-called two-stage approach, in which the first stage involves specification and estimation of the stochastic frontier production function and prediction of technical inefficiency effects under the classical assumption that they are identically distributed. One serious problem occurs in the second stage where the predicted technical efficiencies are regressed against some explanatory variables, contradicting the *distributional* assumptions used in the first stage. The model used here tries to deal with this by simultaneously estimating the parameters of the stochastic frontier and the inefficiency residual.

Assuming there is a time effect manifested in the technology of the Swedish banking sector, we include a time variable in the functional form of the frontier. The slope of the time variable (the time trend) will indicate the direction of technical change in the banking industry.

Let us also assume (as in Battese and Coelli, 1995) that u_{it} is a non-negative random variable associated with technical inefficiency of production, such that u_{it} is

obtained by truncation of the normal distribution with mean $z_{it}\delta$ and variance σ_u^2, where z_{it} includes a variable for the amount of IT investment and a time variable as well as an intercept. The first estimated model will then be as follows:

$$\ln y_{it} = \beta_o + \sum \beta_n \ln x_{nit} + v_{it} - u_{it}$$
$$u_{it} = z_{it}\delta + w_{it} \qquad\qquad (0.1)$$

The random variable w_{it} in the equation $u_{it} = z_{it}\delta + w_{it}$ is defined by the truncation of the normal distribution with 0 mean and variance σ_w^2, such that the point of truncation is $-z_{it}\delta$ (so $w_{it} > -z_{it}\delta$). This will make the distribution for u_{it} to be a non-negative truncated normal $N(z_{it}\delta, \sigma_u^2)$.
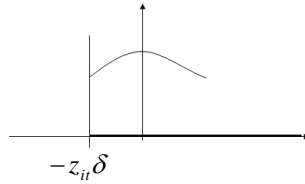

Figure 2. PDF of w_{it} variable, $w_{it} \in N(0, \sigma_w^2)$
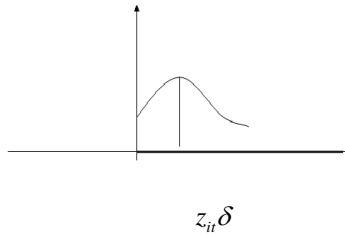
Figure 3. PDF of u_{it} variable, $u_{it} = z_{it}\delta + w_{it} \Rightarrow u_{it} \in N^+(z_{it}\delta, \sigma_u^2)$

The parameters δ_i from the inefficiency function $u_{it} = z_{it}\delta$ indicate the effects of the corresponding variables on efficiency. A negative value of δ_i indicates a positive effect on efficiency, while a positive value shows a negative effect on efficiency (i.e. increasing inefficiency). The absolute magnitude of the effect on

inefficiency (efficiency) is, however, difficult to quantify as will be shown in the derivation below. Consequently, elasticity is also difficult to recover.

If we define $\mathbf{e} = \mathbf{v}-\mathbf{u},$ where $\mathbf{v}$ and $\mathbf{u}$ are the residuals entering the production frontier (the it index is dropped for convenience), then the joint distribution function for $\mathbf{e}$ and $\mathbf{u}$ is:

$$f_{e,u}(e,u) = \frac{\exp\left\{-\frac{1}{2}\left[\left[(u-\mu_*)^2/\sigma_*^2\right]+\left[(e+\mathbf{z\delta})^2/(\sigma_v^2+\sigma_u^2)\right]\right]\right\}}{2\pi\sigma_u\sigma_v\Phi(\mathbf{z\delta}/\sigma_u)} \quad (2),$$

where:

$$\mu_* = \frac{\sigma_v^2 \cdot \mathbf{z}\,\boldsymbol{\delta} - \sigma_u^2 \cdot e}{\sigma_v^2 + \sigma_u^2} \quad (3)$$

$$\sigma_*^2 = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_u^2} \quad (4)$$

It can be shown that:

$$f_e(e) = \frac{\exp\left\{-\frac{1}{2}\left[(e+\mathbf{z\delta})^2/(\sigma_v^2+\sigma_u^2)\right]\right\}}{\sqrt{2\pi\left(\sigma_v^2+\sigma_u^2\right)}\,\Phi(\mathbf{z\delta}/\sigma_u)\Big/\Phi(\mu_*/\sigma_*)} \quad (5)$$

Following this,

$$f_{u|e}(u\mid e) = \frac{f_{e,u}(e,u)}{f_e(e)} = \frac{\exp\left\{-\frac{1}{2}\frac{(u-\mu_*)^2}{\sigma_*^2}\right\}}{\sqrt{2\pi}\sigma_*\Phi(\mu_*/\sigma_*)} \quad (6)$$

Then,

$$E(u\mid e) = \mu_* + \sigma_*\frac{\phi(\mu_*/\sigma_*)}{\Phi(\mu_*/\sigma_*)} = \sigma_*\left(\frac{\mu_*}{\sigma_*} + \frac{\phi(\mu_*/\sigma_*)}{\Phi(\mu_*/\sigma_*)}\right) \quad (7).$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ represents the CDF and the density function of the standard normal random variable.

Consequently, the marginal effect of z_k on $E(u|e)$ can be shown as:

$$\frac{\partial E(u|e)}{\partial z_k} = \delta_k\left\{1 - \frac{\mu_*}{\sigma_*}\left[\frac{\phi(\mu_*/\sigma_*)}{\Phi(\mu_*/\sigma_*)}\right] - \left[\frac{\phi(\mu_*/\sigma_*)}{\Phi(\mu_*/\sigma_*)}\right]^2\right\} \quad (8).$$

It can be proven that the expression in the curly brackets is positive. The sign of the marginal effect of z_k is then given by the sign of δ_k. Consequently, we will obtain a maximum-likelihood estimate of δ_k.

It is important to mention that the model proposed here uses a parameterisation of only the mean of u_{it}, although both the mean and the variance could just as well have been parameterised, as in Wang (2002). The variance would then have been expressed as $\sigma_{it}^2 = \exp(z_{it}\delta)$. An advantage of using this alternative approach would have been its ability to express a non-monotonic relationship between the z_k variables and efficiency. A non-monotonic relationship divides the parameter space into regions where there is a positive impact on efficiency and regions where there is a negative impact. For instance, it is presumable that age has a positive impact on individual performance up to a certain limit, after which the impact becomes negative. The model used here only allows for a monotonic relationship between exogenous variables and efficiency.

2.1 An alternative specification

A second model that we estimate has the following specification:

$$
\begin{aligned}
\ln y_{it} &= \alpha_i + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \\
u_{it} &= z_{it}\delta + w_{it}
\end{aligned}
. \qquad (2.1)
$$

This model (dubbed 'true fixed effects model' in Greene, 2004) accounts for potential bank heterogeneity through the introduction of a bank-specific intercept. The reason for doing this is that we may want to account for firm-specific variables that should not be labelled as inefficiencies or efficiencies, i.e. 'environment variables' that influence the output directly but not necessarily through efficiency as defined by Farrell (1957). In this context one might ask what makes us consider *IT expenditure* as an exogenous factor influencing efficiency. Obviously, *IT expenditure* is a variable subject to manager's decision. However, since it is not clear how it relates to the output of banks, we consider it an "environmental" variable.

Through the introduction of a bank-specific intercept together with non-negative technical inefficiencies – viewed as linear functions of variables involving firm characteristics – we will absorb part of the heterogeneity from the residuals into intercepts. It will be interesting to see how much. We also want to see what is left for the residuals to explain after most specific effects are incorporated in the intercepts.

The estimation of Model (2.1) can still be done by maximum likelihood simply by fitting firm-specific dummy variables. This particular solution is not feasible when we deal with a large number of cross-sections, mainly due to the dramatic loss of degrees of freedom and secondly because of the computational demand.

Another even more difficult problem with this kind of approach is the so-called 'incidental parameters problem', first signalled in Neyman and Scott (1948). In brief, when we have a number of 'structural' parameters (pertaining to the whole population), and also some 'incidental' parameters (the firm-specific α_i), one can show that the ML estimates of the structural parameters need not be consistent.

To estimate this second model, Greene (2004) proposes a 'brute force' technique that relies on some convenient matrix algebra used in the context of Newton's iterative method:

$$\begin{pmatrix} \hat{\gamma} \\ \hat{\alpha} \end{pmatrix}_k = \begin{pmatrix} \hat{\gamma} \\ \hat{\alpha} \end{pmatrix}_{k-1} - \mathbf{H}_{k-1}^{-1}\mathbf{g}_{k-1} = \begin{pmatrix} \hat{\gamma} \\ \hat{\alpha} \end{pmatrix}_{k-1} + \begin{pmatrix} \Delta_{\gamma} \\ \Delta_{\alpha} \end{pmatrix} \quad (9),$$

where $\gamma = [\beta, \delta]$, α is the bank-specific intercept, and $\mathbf{H}$ and $\mathbf{g}$ are the Hessian and the gradient of the log-likelihood function, respectively. One can also attain an easily computable asymptotic covariance matrix for the slopes and for the constant terms.

Since our limited data set (85 units and 425 observations) allows for it, we make use of the simplest approach, i.e. fitting dummies into the production frontier and performing a maximum likelihood estimation of the second model.

Further work is required for assessing the properties of this model, e.g. the robustness of the estimators. Greene (2005) presents encouraging results for the behaviour of this type of estimator.[2]

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[2] The results concern mainly the severity of the biases induced by the 'incidental parameters problem'. His Monte Carlo simulations were not able to show a clear behavioural pattern for these estimates.

We could specify the α_i as stochastic variables as in Greene (2005) with the same distribution, i.e. consider some sort of random effects model. This would require accepting the assumption that these individual effects are *not* correlated with the regressors in the production frontier, which is a rather strong assumption in this context. A Hausman test[3] for random effects (not reported here) also indicates rejecting the null hypothesis of random effects.

It is interesting to see how much of the variation of the residuals is left in comparison with the first model and how the efficiency scores change. We would expect all the banks to appear more efficient, since part of the inefficiency effect is absorbed into the fitted intercepts. However, as the results show, this may not be the case for all banks, although the overall mean efficiency is higher than in the first model (1.1).

3. The data

A panel of data obtained from 1999-2003 annual reports of 85 Swedish banks is used. The sample covers virtually the whole Swedish banking system at the time of investigation.[4] The time span was restricted by the available information concerning IT expenses.[5]

The value of gross revenues, labour expenses, inventories, IT expenses, and the number of branches was registered for each bank. The large variation in the number of branches, reflecting heterogeneity in the scale of operation, might cause heteroscedasticity concerns. To avoid this problem, the data is normalised with the number of branches for each bank. The resulting values are then transformed as log values.

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[3] As described in Hsiao (2003), p.50-51.
[4] We do not, however, cover the foreign-owned banks active in Sweden. Their share was relatively small during the period mentioned.
[5] Data comes from the Annual Reports of banks. IT expenditure is registered separately since 1999. The banking sector in Sweden was very turbulent in the beginning of the 1990s, so we actually cover a period that was relatively smooth for the Swedish banking sector; see Gjirja (2004) for details.

Table 1. Descriptive statistics*

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Gross_rev	421	19251.0	15737.8	831.01	174602
Labor_cost	421	6508.98	10280.2	269.0	114785
Inventories	421	1114.29	1488.79	7.56	17855.6
Buildings	421	3154.02	3549.97	0	26006.3
Deposits	421	316357	283912	25673.2	2267840
IT_costs	418	1820.23	1562.08	0	13969.1
Branches	421	21	86	1	640

* all values are in thousand SEK, where appropriate.

Two main approaches are used in the empirical studies on banking: the so-called '*intermediation approach*' and the '*production approach*'. The former views banks as intermediates of financial services; outputs are measured in money, and costs are defined to include both interest expense and total production costs. The difference in the latter approach is that total costs exclude interest expenses and that outputs are measured by the number of accounts serviced as opposed to money values, since banks are considered as producers of loan and deposit account services using capital and labour. Since this study maintains a kind of intermediation view, deposits are used as an input and revenues as an output. For a discussion about choice of inputs and outputs in banking, see Mlima and Hjalmarsson (2002).

The output is considered *gross revenues*, meaning that it includes: *fees and commissions, net interest revenues and other assimilated financial revenues (e.g. dividend income and the net result of financial operations). Gross revenues* is treated as a money value proxy for the output of a bank's activity. The discussion of an appropriate output for the banking industry is complex and no consensus is yet reached (Triplett and Bosworth, 2004). This alternative is proposed since revenues are considered to be a satisfactory description of the outcome of bank activity. Moreover, it is difficult to assume a single price level for the output of banks. In addition to this, some services provided by banks are not directly priced.

The *IT expenditure* variable includes costs related to equipment (hardware), software acquisition, consulting and training. Since we only have an aggregate of IT expenses, we assume that they stand for a bulk of IT capital. While it is true that IT capital is a stock measure and expenditures are a flow measure, we nevertheless find that expenditures are a reasonable proxy since the depreciation rate of IT capital is very high.

There have been numerous studies concerned with deriving an adequate measure for IT capital (see Brynjolfsson, 1993, for a review). The many authors have tried various proxies (e.g. power of calculus), but none has turned out very satisfactory. Hence, the amount of expenses is used here as a reasonable approximation of IT capital.

As mentioned before, the production frontier includes a time trend in order to capture technical change as expressed by shifts in the production frontier. Other variables (inputs) that be considered are: *deposits, inventories, buildings* and *labour* (expressed as number of work hours). The *IT expenditure* variable will enter the underlying mean of the inefficiency effect u_{it}.

4. Estimation results

A preliminary step in the empirical analysis is to estimate a traditional pooled regression, with *IT expenditure* among the inputs. A panel-data model where the structure of the inefficiency term is given by a half-normal distribution (i.e. $u_{it} \in N^+(0, \sigma_u^2)$) is estimated as well. Table 2 presents the results. These specifications serve as a benchmark for Models (1.1) and (2.1). It should be noted that the negative coefficient for the time variable indicates a downward shift of the production frontier for the banking industry over the period studied. This shift is undoubtedly related to the economic conditions 1999-2003 in Sweden (mild recession and the burst of the IT bubble). The estimated slope for *IT expenditure* is not statistically significant, making it a poor candidate as an ordinary input in the production function of the banking sector.

Lambda is defined as σ_u / σ_v and sigma as $\sqrt{\sigma_v^2 + \sigma_u^2}$. Obviously, a large value of lambda implies that the variation in inefficiency effects is important relative to total variation. Although the lambda values are very small, the estimates are statistically significant.

Table 2. The first column in this table shows the estimates for the pooled regression, when IT expenditure is included among the inputs used in the production frontier. The low significance of the estimated coefficient shows that our dataset does not favour the view of IT expenditure as an ordinary production factor, along with the traditional ones. The negative value of the time trend coefficient points to the fact that the technology describing the Swedish banking industry has experienced a slightly negative technical change during the analysed period. This is likely related to the moderate economic recession that was registered at the beginning of this decade.

Parameter values	Pooled regression. (*IT expenditure* is among inputs)	Panel data model. (u_{it} distribution is half-normal)
Production frontier param.		
Intercept	.0672***	
	(.554)	
$Log(L_{it})$	.567***	.557***
	(15.63)	(15.625)
$Log(Inv_{it})$	.078***	.082***
	(4.91)	(6.068)
$Log(B_{it})$	.413E-04	.0004
	(1.534)	(.083)
$Log(D_{it})$	.354***	.359***
	(11.27)	(16.54)
$Log(IT)$	.164E-03	.561E-3
	(1.373)	(.047)
$Year_t$	-.011*	-.011*
	(-1.74)	(-1.64)
Lambda	1.123***	.279***
	(8.158)	(24.16)
Sigma	0.204***	1.17***
	(543.787)	(4.6)
Log-likelihood	165.97	203.38
σ_v	0.135	0.181
	-	
σ_u	0.152	0.213
	-	

[i] The values in parentheses are the corresponding t-ratios for each parameter estimate.
[ii] *, ** and *** correspond to a 1%, 5% and 10% level of significance, respectively.

Table 3 presents the results of estimating Models (1.1) and (2.1). Model (1.1) has the form:

$$\ln(Y_{it}) = \beta_o + \beta_1 \cdot \ln(L_{it}) + \beta_2 \cdot \ln(Inv_{it}) + \beta_3 \cdot \ln(B_{it}) + \beta_4 \cdot \ln(D_{it}) + \beta_5 \cdot Year_i + v_{it} - u_{it} ,$$

where technical inefficiency effects are assumed to be defined by

$$u_{it} = \delta_0 + \delta_1 \cdot \ln(IT_{it}) + w_{it}$$

,

and where $i = 1,..., n$ represents the bank and $t = 1,...,4$ the time variable.

Y_{it} is the total value of output (gross revenues),

L_{it} is labour expense,

Inv_{it} is the value of fixed assets except buildings.[6]

B_{it} is the value of buildings and

D_{it} is the value of deposits (stock value).

IT_{it} is the amount of expenditure related to maintaining an IT banking system (the cost of equipment, software, consultancy for implementing specialised software and the cost of training IT personnel) and $Year_t$ is a time trend.

As already mentioned, the method of maximum likelihood is proposed for the simultaneous (i.e. one-step) estimation of the parameters of the stochastic frontier and the model for technical inefficiency effects.

The second model (2.1) has a specification similar to the first, except for the intercepts, which are now bank specific:

$$\ln(Y_{it}) = \alpha_i + \beta_1 \cdot \ln(L_{it}) + \beta_2 \cdot \ln(Inv_{it}) + \beta_3 \cdot \ln(B_{it}) + \beta_4 \cdot \ln(D_{it}) + \beta_5 \cdot Year_t + v_{it} - u_{it}$$
$$u_{it} = \delta_0 + \delta_1 \cdot \ln(IT_{it}) + w_{it}$$
.

Using available software for maximum likelihood functions, estimation is done with the mentioned 'brute force' technique, despite the sparse nature of the regressors matrix due to the high number of dummy variables.

The negative sign of the parameter estimate related to *IT expenditure* shows there they have a positive influence on efficiency i.e. a greater value of *IT expenditure* leads to a decrease in firm inefficiency. The conclusion that follows from this finding is that intensive use of IT capital increased the efficiency of Swedish banks over the studied time period. There is a persistent effect of IT expenses on firm (in)efficiency, but the associated elasticity of the effect is not reported here. However, the negative slope of the time trend included in the frontier model indicates that there is a negative technical change at the frontier over the studied time period. Despite this, there is a positive impact of *IT expenditure* on the individual efficiency scores.

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[6] The parameter is not found to be statistically significant in any of the estimated models, maybe due to the fact that many banks do not actually own buildings.

Table 3. The first column in this table presents the estimates for the panel data model without bank-specific effects, while the second column presents the estimates for the panel data model when bank-specific effects are introduced. The negative slope coefficient for log (ITit) indicates a positive effect of IT capital on the efficiency of banks.

Parameter values	Model 1.1. Common intercept	Model 2.1. Bank-specific intercept i.e. the true fixed-effects model
Production function variables		
Intercept	0.236***	See the list of firm-specific
	(3.64)	effects in the Annex
Log(L_{it})	0.59***	0.58***
	(19.1)	(15.81)
Log(Inv_{it})	0.063***	0.026***
	(3.824)	(2.232)
Log(B_{it})	0.0033	-0.0005*
	(1.008)	(-2.089)
Log(D_{it})	0.304***	0.39***
	(13.10)	(10.79)
Year$_t$	-0.061***	-0.031***
	(-2.23)	(-8.40)
Inefficiency determinants		
Intercept	0.253***	-2.12***
	(7.04)	(-3.071)
Log(IT_{it})	-0.066***	-0.035***
	(-5.388)	(-5.096)
Lambda		15.62***
		(3.061)
Sigma		0.42***
		(3.99)
σ_v		0.027
σ_u		0.422
γ		
Log-likelihood	537.67	527.52
LR test (nr restr. = 3)	43.58	

[i] The values in parentheses are the corresponding t-ratios for each parameter estimate.
[ii] *, ** and *** correspond to a 1%, 5% and 10% level of significance, respectively.

Again, lambda is defined as σ_u/σ_v and sigma as $\sqrt{\sigma_v^2+\sigma_u^2}$. The large value of lambda implies that the variation in inefficiency effects is important relative to total variation. The estimate is statistically significant.

The main interest here is in the structural parameters used to assess the impact of IT capital on the efficiency of Swedish banks. However, one important advantage of the proposed specifications, that use the panel nature of the data set, is that we can obtain *efficiency scores* for each bank and for each period. The technical efficiency of production for firm *i* in period *t* would be given by:

$$TE_{it} = E\left[\exp(-u_{it})\,|\,e_{it}\right]$$.

Using the JMLS (Jondrow, Lovell, Materov, and Schmidt, 1982) estimator, adapted for panel data as in Batesse and Coelli (1995), we can then recover firm and time-specific efficiencies:

$$TE_{it} = E\left[\exp(-u_{it}) \mid e_{it}\right] = \frac{\Phi\left[(\mu_* / \sigma_*) - \sigma_*\right]}{\Phi\left[(\mu_* / \sigma_*)\right]} \exp\left[-\mu_* + \frac{1}{2}\sigma_*^2\right]$$

(σ_* and μ_* were defined in Section 2).

This paper does not report estimated values of efficiency for individual banks, but arithmetic means for the efficiency of the Swedish banking sector have been calculated for both Models (1.1) and (1.2).

The overall mean efficiency for the first model is 0.874, while for the second model it increases to 0.912. This increase is expected given that part of the heterogeneity that was previously included in the residuals is now absorbed into the firm-specific effects. However, this is not true for all banks. Some have experienced decreases in efficiency after including a specific effect.

A test for the existence of inefficiency effects and for the appropriateness of our modelling is done as a likelihood ratio test, with the null that inefficiency effects are absent from the model. That is:

$$H_0 : \lambda = \delta_0 = \delta_1 = 0.$$

The statistic *-2[log(likelihood(H_0)\likelihood(H_1))]* has to be chi-square distributed with 3 degrees of freedom. Our calculated value of 43.58 (for the first model) leads to a rejection of the null hypothesis.

5. Concluding remarks

This paper investigates whether increased adoption of new technologies (i.e. use of IT capital) had an impact on the efficiency of Swedish banks, during 1999-2003. To this end, the impact of *IT expenditure* on bank efficiency is analysed using a model that considers the exogenous influence of *IT expenditure* on efficiency through the specification of an inefficiency variable u_{it} distributed as truncated $N(z_{it}\delta, \sigma^2)$, where z_{it} is a vector of exogenous variables affecting efficiency. A second model that accounts for bank heterogeneity through the introduction of fixed effects is also

proposed and estimated, and similar findings emerge, i.e. bank efficiency increases when employing more IT capital.

The main finding is a negative value for the marginal effect of *IT expediture* on the inefficiency residual, which in turn shows a positive effect on bank efficiency. This positive effect is exerted during a period when there was an overall negative technical change in the banking sector's production frontier. The possibility of disentangling the positive effect of an exogenous variable on technical efficiency, despite an overall negative technical change, is due to the use of a stochastic frontier model with a specification similar to that in Battese and Coelli (1995).

One shortcoming of the paper could be the use of *gross revenues* as a proxy for output of bank activity. However, the paper does state some arguments for why this could be considered appropriate.

One important aspect of banking activity, not addressed in this paper, is the level of risk associated with the banks' assets. It is possible to calculate a risk index for the overall activity of banks, but this is a tedious task. Large banks can usually provide a calculated risk index, but no such information is usually available for small banks or for branches. The risk exposure of a bank obviously influences its output and consequently conclusions about bank efficiency at a certain moment in time. One way to deal with this problem is to include the risk index of the bank's balance sheet as an input in the production function, when this information available. Wang (2003) discusses in great detail methods to adjust for risk when measuring bank output.

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Annex

Fixed effects estimates

	Value	Std. Err.	P-value		Value	Std. Err.	P-value
IDNR001	-.20206	-1.405	.1599	IDNR044	0.084524	1.666	0.0958
IDNR002	0.24904	5.723	0	IDNR045	0.098022	2.032	0.0422
IDNR003	0.030367	0.659	0.51	IDNR046	-0.13974	-0.565	0.5722
IDNR004	-0.04509	-0.879	0.3792	IDNR047	-0.43707	-1.748	0.0805
IDNR005	0.055467	1.162	0.2452	IDNR048	-0.728	-2.913	0.0036
IDNR006	0.025925	0.604	0.5459	IDNR049	0.420036	7.194	0
IDNR007	0.042158	0.696	0.4865	IDNR050	0.080302	1.844	0.0652
IDNR008	0.006261	0.114	0.9093	IDNR051	0.0267	0.542	0.5879
IDNR009	-0.01396	-0.297	0.7667	IDNR052	-0.24397	-5.508	0
IDNR010	0.078405	1.446	0.1481	IDNR053	0.161859	3.454	0.0006
IDNR011	-0.6273	-2.508	0.0121	IDNR054	-0.23349	-4.741	0
IDNR012	-0.04691	-0.828	0.4075	IDNR055	-0.10922	-2.237	0.0253
IDNR013	-0.01247	-0.23	0.8182	IDNR056	0.084993	1.783	0.0745
IDNR014	-0.27149	-4.569	0	IDNR057	-0.07639	-1.728	0.084
IDNR015	0.173934	3.664	0.0002	IDNR058	0.034559	0.714	0.4753
IDNR016	0.128752	2.838	0.0045	IDNR059	-0.1854	-4.211	0
IDNR017	-0.01174	-0.261	0.7942	IDNR060	0.201092	4.371	0
IDNR018	-0.71042	-2.777	0.0055	IDNR061	0.075955	1.693	0.0904
IDNR019	0.001657	0.034	0.9728	IDNR062	0.041958	0.918	0.3585
IDNR020	-0.10903	-2.359	0.0183	IDNR063	-0.00217	-0.05	0.9603
IDNR021	-0.34675	-6.483	0	IDNR064	0.057674	1.304	0.1922
IDNR022	-0.02173	-0.421	0.6738	IDNR065	0.10658	2.396	0.0166
IDNR023	-0.21996	-4.783	0	IDNR066	0.029279	0.529	0.5966
IDNR024	0.190372	4.276	0	IDNR067	0.02784	0.588	0.5569
IDNR025	0.081663	1.483	0.138	IDNR068	0.097736	2.17	0.03
IDNR026	0.200555	3.611	0.0003	IDNR069	0.295491	6.15	0
IDNR027	-0.06151	-1.383	0.1668	IDNR070	-0.07811	-1.432	0.1523
IDNR028	-0.29147	-1.172	0.2411	IDNR071	-0.41154	-1.606	0.1084
IDNR029	0.021934	0.462	0.6443	IDNR072	0.070921	1.602	0.1092
IDNR030	0.67626	1.495	0.135	IDNR073	0.027454	0.571	0.5681
IDNR031	0.083922	1.886	0.0593	IDNR074	-0.03094	-0.586	0.558
IDNR032	0.054248	1.008	0.3134	IDNR075	0.212238	4.753	0
IDNR033	0.143477	2.853	0.0043	IDNR076	0.337597	6.201	0
IDNR034	-0.01358	-0.301	0.7633	IDNR077	0.064435	1.408	0.1591
IDNR035	0.18594	4.078	0	IDNR078	0.279499	5.583	0
IDNR036	0.159926	3.361	0.0008	IDNR079	0.35367	7.893	0
IDNR037	0.074098	1.604	0.1087	IDNR080	0.005897	0.128	0.8981
IDNR038	0.061878	1.108	0.2677	IDNR081	0.136397	2.831	0.0046
IDNR039	0.058217	1.136	0.2561	IDNR082	-0.13993	-2.468	0.0136
IDNR040	0.260343	5.459	0	IDNR083	0.149956	2.881	0.004
IDNR041	0.022625	0.455	0.6492	IDNR084	-0.45067	-1.816	0.0693
IDNR042	-0.55437	-2.222	0.0263	IDNR085	0.089954	1.914	0.0557
IDNR043	0.170925	3.196	0.0014				

Paper IV

Are all DMUs efficient in DEA? DEA meets the vintage model.

Constantin Belu[*]

Abstract

In this paper I develop a model of capacity expansion that accounts for differences in the productivity of the installed capital due to technical progress exhibited by the *ex ante* production function. A putty-clay set-up is assumed, meaning flexible input coefficients and substitution possibilities *ex ante*, but fixed input coefficients *ex post*. Based on the model, I generate a capacity distribution of DMUs (vintages) for a homogenous industry and perform an efficiency analysis employing data envelopment analysis, a popular non-parametric method for estimating efficiency. The results show that in some circumstances older vintages might appear on the efficiency frontier, unlike some newer vintages that are found to be inefficient, despite benefiting from the advancement of the technology.

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1. Introduction

Following the seminal article by Farrell (1957) on the measurement of productive efficiency, several contributions appeared in the 1960s and the 1970s. However, the field did not really take off until the 1980s, due to some very important contributions on the methodological and conceptual side in the previous decades; see Forsund and Sarafoglou (2005) for a study of the diffusion of research on productive efficiency.

Farrell (1957) applied a nonparametric deterministic programming model to measure the distance, that he called *technical efficiency*, from a best-practice frontier to a set of decision-making units (DMUs) in a constant returns to scale (CRS) framework. Aigner and Chu (1968) showed how to measure such a distance for a homogeneous parametric Cobb-Douglas (CD) production function by simple linear (or quadratic) programming, although their focus was more on the frontier function itself than on efficiency measurement This parametric deterministic frontier approach (DFA) was generalised by Forsund and Hjalmarsson (1979a) to non-homogeneous, variable returns to scale (VRS) production functions.

In Farrell's approach all efficiency scores were calculated simultaneously by solving a rather complicated programming problem. A much more tractable approach was suggested by Charnes, Cooper and Rhodes (1978), CCR, (although Forsund and Sarafoglou (2002) discovered that the complete CCR model was presented already in Boles (1971) in an unpublished working paper). By solving a simple programming problem, efficiency scores could be obtained for one DMU at a time. The method was coined Data Envelopment Analysis (DEA) and is now not only the dominant non-parametric approach to efficiency measurement but probably also the overall dominant approach to efficiency measurement. Forsund and Sarafoglou (2002) and (2005) discuss the evolution of the concept of frontier production function that links Farrell's work with modern DEA.

In parallel with the development of the deterministic strand, an alternative stochastic strand of efficiency measurement gradually progressed from a first important contribution by Afriat (1972) who formulated a statistical framework for finding maximum likelihood estimators for the parameters of the frontier function. The real

breakthrough was the seminal contributions of the composed error stochastic frontier analysis (SFA) by Aigner et al. (1977), Meeusen and van den Broeck (1977) and, with reference to Aigner et al. (1977), Battese and Corra (1977), based on the distinction between inefficiency and random noise. This approach has been further developed in panel data modelling into different models of time-varying and time-invariant efficiency; see Kumbhakar and Lovell (2000). Moreover, by bootstrapping procedures, DEA has also developed towards a stochastic approach; see e.g. Simar and Wilson (2000) and (2008). The increased availability of micro-level panel data sets has facilitated both new theoretical developments and empirical studies concerned with explaining the evolution of an industrial sector over time. However, almost all efficiency studies seem to be based on an ad hoc specification of the efficiency distribution.

After all, the basic efficiency concept has not changed. Although input- and output-oriented efficiency and scale efficiency (Forsund and Hjalmarsson, 1974 and 1979b) and non-radial efficiency measures (Fare and Lovell, 1978) have been introduced, the distance from a DMU to the frontier is still called technical efficiency, while the distance to optimal scale at the frontier is called scale efficiency. An extensive discussion on the evolution of efficiency measurement techniques and related concepts i.e., minimum scale size (MSS), most productive scale size (MMPS), etc., is provided in Forsund and Sarafoglou (2005).

The point made in this paper is that an efficiency score is a distance measure and that an efficient unit may not be very efficient in a more normative sense. This point is not related to the statistical uncertainty about a specific efficiency score. It is directly related to the basic notion of efficiency and the interpretation of efficiency scores. My impression of the efficiency literature is that many authors seem to neglect that technical efficiency is a distance measure and not an efficiency measure per se. To make my point in this paper I will, based on a putty-clay model, first generate an efficiency distribution with a clear vintage structure of DMUs and then calculate the efficiency scores of the DMUs. Since the model is a model of optimal capacity expansion it generates a specific ranking of efficiency among the DMUs. Recent vintages are more efficient than older ones. The issue addressed is to what extent DEA manage to pick up this predetermined ranking of efficiency.

Thus, I first exploit a stylised model of capacity expansion in a homogeneous industry such that I explicitly account for embodied technical progress, the putty-clay nature of the capital and the impact of a vintage effect on the capacity distribution, and then I use the generated set of units to conduct a DEA analysis, with the aim to show that DEA is not able to retrieve the 'correct' distribution of efficiency. Although this point may seem obvious, I am not aware of any paper that has shown it clearly. On the contrary, my firm impression is that most researchers interpret the efficiency scores in a normative way, even in policy recommendations.

In the modern literature concerned with the measurement of productive firms' performance, most studies resort to deterministic techniques like DEA, or to stochastic models like SFA. These techniques rely on an observed sample, i.e. technically-feasible outcomes that are actually realised, to construct an industry average and an industry *best practice*. However, these observed values do not cover the whole production possibility set. Hence, theoretical models of the production possibilities set could provide insights unattainable through empirical research. These latent production possibilities could provide us with better insights regarding the industry dynamics.

My model is a modest attempt to provide some insights on the efficiency distribution of the installed capacities in a homogenous industry by considering the putty-clay nature of the capital and the vintage effect. I believe that the technical constraints a firm faces at every moment in time are important in determining firm behaviour and productivity.

The remainder of the paper is organised as follows: The next section presents a brief review of the literature related to putty-clay. Section 3 presents my theoretical model. Section 4 discusses the simulation strategy. Section 5 provides the results of the DEA analysis, and Section 6 concludes the paper.

2. A brief literature review related to putty-clay

Many economists have been concerned with the putty-clay nature of capital and have worked on models that take this property into account. I do not intend to provide a comprehensive literature review, but do want to point out some of the most influential

papers written in connection with the topic and also present some of the most recent studies. While the putty-clay nature of capital is mainly encountered in models of economic growth, it is also seen in research concerned with the optimal structure of an industry and optimal timing of investments.

The elasticity of a firm's supply curve depends crucially on the firm's technical possibilities. Technology is described by a few key factors: substitutability of inputs and outputs for one another, the vintage effect caused by embodied technical progress, the nature of returns to scale and expectations about future demand growth and development of relative prices.[2] The vintage effect links the technical performance with time. In this paper I will assume that embodied technical progress makes more recent technologies more efficient than older ones.

Johansen (1959) is a seminal paper presenting a growth model that builds on the hypothesis of substitution possibilities *ex ante*, but no such possibilities *ex post*. While Johansen (1959) focused on "warranted growth", Solow (1962a) was more oriented towards the heated capital-theoretic debate between Cambridge Massachusetts and Cambridge UK. (The first two sentences of this paper read: "I have long since abandoned the illusion that participants in this debate actually communicate with each other. So I omit the standard polemical introduction, and get down to business at once.") On the other hand, Solow (1962b) is more directly focused on growth and embodied technical progress and especially the relation between investment and growth, emphasising the importance of the putty-clay approach (Solow 1962b, p. 78):

> If it is assumed (...) that labor and already existing capital are substitutable for each other, then in principle capital should never be idle unless its marginal value product has fallen to zero. (…) Otherwise it would pay to use more capital with the current input of labor; the extra product would provide at least some quasi-rent. Yet we believe there to be such a thing as idle capacity in periods of economic slack. The paradox is easily resolved in a model which permits virtual substitution of labor and capital before capital goods take concrete form, but not after.

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[2] Through 'vintage effect' I would like to define all the differences existent between installed capital at different moments in time, especially regarding productivity. This requires the model to specifically account for each vintage.

Solow also underlined that it is difficult to use the concept in empirical work. One drawback of the putty-clay approach is the lack of appropriate data for empirical analysis. However, today micro-level panels are becoming increasingly available (e.g. the Longitudinal Research Database maintained by the US Bureau of Census). Bartelesman and Doms (2000) offer a comprehensive review of the empirical work related to the measurement of productivity and its determinants when panel data is available.

Furthermore, Solow (1962b) analyses the properties of this model through computer simulations and one of his findings is that technologies that do not allow substitutability between labour and capital in the short run do permit substitutability in the long run. Moreover, he claims that empirical estimates of production functions may give indications of increasing returns when there are none.

Phelps (1963) builds on a growth model that considers the putty nature of capital *ex ante* but clay *ex post* (after the investment has been realised). He is considered to have coined the terms 'putty' and 'clay'.

The putty-clay model did not really take a final step into a dynamic theory of production until Johansen (1972). As an intermediate step from Johansen (1959), Johansen (1967) investigates the optimal choice of factor proportions in an industry characterised by putty-clay, not from a growth perspective but from an industry-planning perspective[3]. Inspired by Salter (1960) and Houthakker (1955), Johansen (1972) introduced a formal vintage (or putty-clay) theory of production that distinguishes between *ex ante* and *ex post* micro production functions and between the short-run and long-run macro (industry) production functions. Putty-clay refers to the fact that a firm has flexibility in its choice of technology (i.e. input coefficients and capacity) before investment (full substitutability of factors *ex ante*) but faces fixed factor proportions *ex post*. Since capital costs are sunk costs, only variable inputs and maximum capacity matter in the short-run optimisation. When the quasi-rent of a DMU becomes negative it will be closed down. Hence, firms of different vintages may have different factor proportions and capacity even if the shape of the underlying technology is the same.

The core of Johansen´s production theory is the short-run industry production function built up from the capacity distribution of DMUs. With two or more variable

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[3] As a matter of fact, this is to a large extent also my perspective in this paper.

inputs, substitution possibilities arise, up to full capacity utilisation, from varying degree of capacity utilisation of the different DMUs even if each unit is characterised by fixed coefficients and a fixed capacity.

Thus, unlike the neoclassical model, the putty-clay model generates an explicit efficiency distribution of the DMUs. With a rapid embodied technical progress the differences between the oldest and the most modern DMUs may be quite substantial; see Forsund and Hjalmarsson (1988) and (1992) for studies of the differences between best-practice and average practice in putty-clay industries.

Johansen (1972) was extended in different directions and especially by his assistants and fellow colleagues in Oslo. Hjalmarsson (1973) provided a close scrutiny of the concepts of 'optimal industrial structure' and 'optimal structural change', resorting to putty-clay assumptions about the nature of capital. He points out the difference between the static concept of optimal structure in an industry and the dynamic equivalent of it. The subject is surprisingly topical, given the EU recommendations concerning the implementation of 'best available technology' for newly established plants.[4] Hjalmarsson's (1974) model of optimal capacity expansion provides the theoretical groundwork for the present study and is the backbone of my model. Albrecht and Hart (1983) propose a putty-clay model that they used to investigate the role of uncertainty on investment size. Forsund and Hjalmarsson (1987) is a comprehensive study on industrial structure and optimal structural change, with numerous empirical applications that testify for their conclusions. In a rather unique study of the parallel development of the frontier production function and the short-run industry production function, Forsund et al. (1996) show that striking differences between the two functions may appear when embodied technical progress is important.

Campbell (1998) devises a model of firms based on vintage capital structure, with plants of different vintages experiencing different productivity shocks, as given by a random walk. Consequently, his model departs from mine in the way technical progress impacts firm productivity; my model assumes only a positive effect, while his proposed

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[4] See Council Directive 96/61/EC and Directive 2003/87/EC of the European Parliament and of the Council for recommendations on the implementation of the 'best available technology'.

random walk might make newer vintages perform worse than old ones at some point in time. He uses this micro model of firms for a macroeconomic study of business cycles.

3. The model

The model applied is a stylised model of capacity expansion in the tradition of Manne (1961) and developed by Hjalmarsson (1974), although it seems to generate capacity distributions typically observed for heavy industries in market economies; see Forsund and Hjalmarsson (1987). Thus it has a centralised investment planning perspective rather than a decentralised market perspective. It is a crude model, and there are several extensions and refinements that one could think of. However, for my purpose here I do not need a more refined model.

I assume a homogeneous industry, meaning that there is only one type of output produced by all DMUs. DMUs will determine their investments by choosing to install the capacity that will cover all existing marginal (accumulated) demand. Hence, DMUs will not try to produce more than the market can absorb. This is a key feature of the present model.[5] Obviously, I do not account for the strategic behaviour of firms in oligopolistic markets. Output price will then be completely exogenous. The same consideration will apply to input prices. In a subsequent simulation procedure, I will allow input prices to fluctuate in accordance with a previously specified stochastic process.

Although I am aware of the important theoretical questions about the determinants and timing of investment, it should be noticed that in this study I do not try to shed light on the determinants of investments. Investment decisions are determined exogenously, and DMUs are assumed to posses all the information needed and to have the proper incentives to invest. I focus merely on the technical constraints a DMU faces and the impact of these on its realised investments. My set-up is deterministic, hence uncertainty is assumed to play no role in firms' decisions regarding the optimal installed capacity, although uncertainty may indeed play an important role as shown in Albrecht and Hart (1983), Caballero and Pindyck (1996) and Abel and Eberly (1999).

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[5] This assumption practically implies that DMUs are able to adequately predict the available (accumulated or potential) demand, which in turn implies knowledge about the rate of demand growth and about the market shares of other producers.

There are two factors of production: Capital and Labour, i.e. a fixed and a variable factor. Firms can choose their initial investment based on a technology that is known and available to all producers, and they will set the desired factor proportions in accordance with the prices of inputs that they face at the moment of investment.

Once the investment is made, the capital is sunk and the quantity of labour employed will remain a fixed proportion of the installed capital.
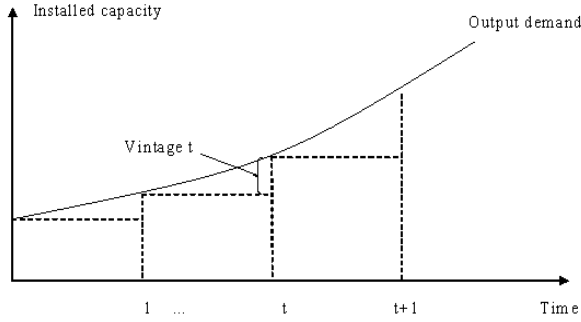

Figure 1

The available technology is assumed to be Cobb-Douglas:

$$(1.1) \quad Q_t = f_t(K_t, L_t, t) = A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta}, \quad \alpha + \beta = \varepsilon.$$

It is important to note that in the above specification, technical progress is *embodied*, i.e. it is explicitly expressed through $e^{\delta \cdot t}$, in a neutral way (Hicks). In order for the embodied technical progress to materialise, investment is required and that means construction of a new plant in my model. The proposed technical progress is of *exogenous* nature. This was made clear when I assumed that all firms have simultaneous access to the new technology.[6]

My modelling strategy takes into account the technology available to firms at a certain moment in time, the moment when the investment decision is taken. I assume that

---

[6] Although this is a restrictive hypothesis, I believe that (as I am concerned with a homogeneous industry) there is sufficient support for this assumption. For instance, technical improvements should rather be equally accessible to all firms; otherwise the firm with a better proprietary technology will soon dominate the market, due to perfect substitutability of output.

firms make investment decisions based on the information currently available and form expectations based on the same information.

Firms make the investment decision at time t based on the existing demand, input prices, and the nature of the production function available for vintage t. I assume that between time $t-1$ and t, there is an accumulation of demand given by the following exponential law:

(1.2) $Q(t) = Q_0 \cdot e^{gt}$.

Then the demand at moment t, which was not covered by previously installed capacities, is:

(1.3) $Q(t) - Q(t-1) = q_0 \cdot e^{gt} - q_0 \cdot e^{g(t-1)} = Q_0 \cdot e^{gt}(1 - e^{-g})$.

Firms will choose optimal quantities of capital and labour, such that the costs implied by the capacity utilisation will be minimised, under the constraint that the output equals the existing unsatisfied demand.

The costs required for the capacity to function are the one-time costs of the one-time installed capital plus the discounted stream of future costs associated with labour use.

(1.4) $C_t = w_K(t) \cdot K_t + \sum_{s=t}^{\infty} w_L(s) L_t \cdot e^{-rt}$,

where r is the risk-free interest rate.

The optimisation programme faced by a firm investing at moment t will then be:

$$\min_{K_t, L_t} C_t = w_K(t) \cdot K_t + \sum_{s=t}^{\infty} w_L(s) \cdot L_t \cdot e^{-rt}$$

(1.5) $such\ as$
$$A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta} = Q_0 \cdot e^{gt}(1 - e^{-g})$$.

Hence, firms enter the market sequentially by taking an investment decision. I assume that the intervals between two successive entries are equal. This is not a restrictive constraint, as long as one knows the dynamics of output demand (e.g. exponential growth). Also, although different instalments can belong to the same firm,

this is not relevant for our analysis since the focus is on plants rather than on firms. Therefore it is reasonable to assume that one plant is one firm. Moreover, it can be allowed that two or more firms to enter the market at the same time as long as it can be agreed on the way they share the available market i.e. output demand. For tractability, I will consider only one entrance at a time.

Every firm will have a newer technology available to choose. This is possible because of the embodied technical change. Before an investment is made, the optimal K^* and L^* are determined by solving programme (1.5). Firms have full flexibility in choosing the desired factor proportions. However, after an investment has been realised, the factors remain in their initial proportions. Plants are assumed to function indefinitely, implying an infinite time horizon. There is no scrapping decision or capital depreciation. While this assumption departs from reality, the purpose of my study is to emphasise the putty-clay nature of capital and its impact on capacity distribution. I am less concerned with the determinants of investment decisions.[7]

Firms will choose their optimal K^* and L^* based on the prices of inputs at the moment of investment. Hence, in calculating the discounted stream of future costs, firms use the wage level at the moment of investment.

This requirement can be relaxed by assuming that firms hold various expectations about the evolution of wage rates and use the expected wage in the optimising programme. For instance, a tractable solution (see Appendix 1) can be found when the wage rate is expected to grow exponentially.

3.1 Scenario 1

I assume that firms use the *actual* wage rate (i.e. firms hold static expectations regarding the wage rate) to calculate the discounted stream of variable costs:

Then programme (1.5) can be written as:

---

[7] Although we would be closer to reality by introducing scrapping into the model, the model would become increasingly intractable. For example, one would need to use information about output price, and we want to avoid this.

$$\min_{K_t, L_t} C_t = w_K(t) \cdot K_t + w_L(t) \cdot L_t \cdot \sum_{s=t}^{\infty} \cdot e^{-rt}$$

(1.6) *such as*

$$A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta} = Q_0 \cdot e^{gt}(1 - e^{-g}) \qquad .$$

The optimal capital to be invested at time t is:[8]

(1.7)
$$K_t^* = \left[\frac{Q_0}{A_0}\right]^{1/\varepsilon} \cdot \left[\frac{\beta}{\alpha}\right]^{\beta/\varepsilon} \cdot \frac{(1-e^{-g})^{1/\varepsilon}}{(1-e^{-r})^{\beta/\varepsilon}} \cdot e^{(g-\delta-r\cdot\beta)t/\varepsilon} \cdot \left[\frac{w_L(t)}{w_K(t)}\right]^{\beta/\varepsilon} ,$$

where $\varepsilon = \alpha + \beta$ is the elasticity of scale and r is the risk-free interest rate, as mentioned before.

For each vintage, an important factor in determining the optimal investment is the relative price of factors. These can change over time, affecting the optimal size. The rate of technical progress is also important, but its importance is counter-balanced by the rate of output demand expansion; for instance, if the rate of technical progress is higher than the rate of output demand expansion, there may be smaller installed capacities for more recent vintages. It is important to recall that I focus on one particular industry, and that different industries might face different evolutions of the relative ratio of input prices and hence different capital (labour) intensities for the same vintage.

4. Simulation of an industry structure

The input prices are exogenous to firms; hence the only time they have an impact on the investment decision is at the moment of investment. Firms observe the actual prices and based on these, they choose the factor ratio and the capacity in which to install by optimising the programme described above. But by simulating a trajectory for the evolution of prices, firms investing at different moments in time will face different input prices and therefore different factor ratios and capacities, as can easily be seen in (1.7).

---

[8] See the Appendix 2 for details.

In all the following simulated scenarios, I will vary the rate of demand growth, the rate of technical progress, the marginal elasticities of labour and capital, the scale elasticity and the evolution of the factor prices, and based on this I will calculate optimal capacities for 20 time periods. Although the optimal investment is determined in a static context, firms are forward looking and account for the evolution of factor prices.

In one set of simulations I will keep a constant rate of change in the input prices. In another set I will assume that the evolution of the factor-price ratio is described by an additive stochastic process (random walk with drift). This means that $d\left(w_L(t)\big/w_K(t)\right) = \mu \cdot dt + \sigma \cdot dZ_t$, where μ and σ, which are parameters describing the process, could in principle be estimated if series of historical values for the wage rate and cost of capital are available. However, we are not interested in doing that, since the main interest is in simulating a *potential* capacity expansion based on a *potential* evolution of prices. Hence, we can assign appropriate parameter values. I do not even imply that the factor-price ratio actually evolves like a random walk with drift, but for this simulation it is a satisfactory equivalent. Z_t is the Wiener stochastic process.
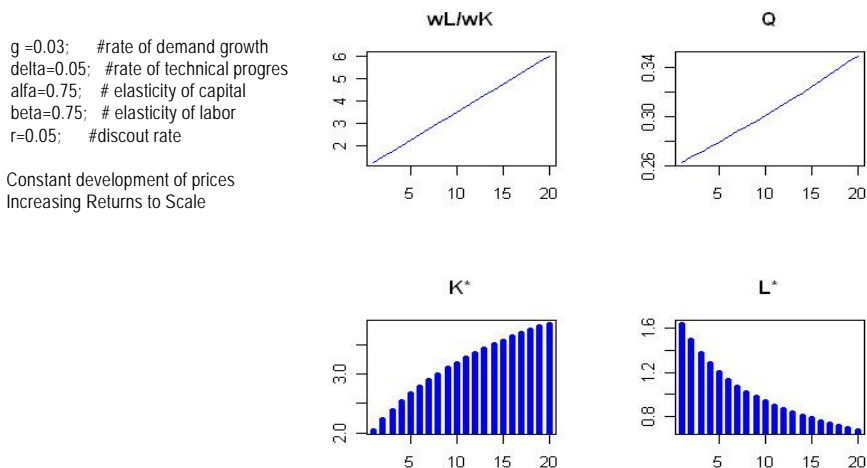
A set of generated capacities is used as DMUs in DEA models similar to Charnes et al. (1978) (CCR henceforth) and to Banker et al. (1984) (BCC henceforth), with appropriate assumptions regarding the returns-to-scale. The aim is to find out which of the generated vintages will appear on the efficiency frontier. I denote the generated DMUs with numbers in accordance with their ages, DMU no. 1 being the oldest and DMU no. 20 the most recent.

5. DEA analysis results

The results will be presented in a set of figures, in the upper part showing the development of the inputs' price ratio (wL/wK), capacity (Q), capital (K) and labour (L) input in each consecutive DMU and in the lower part the different DMUs in the input coefficient space in addition to the CRS and VRS DEA efficiency scores.

Let me start with a set of simulations where I keep a constant rate of change in the input prices. In Case 1, shown in Figure 1, the scale elasticity is rather high, 1.5, the rate of demand growth, 3% and the rate of technical progress 5%.

Figure 1. Simulation Case 1 with increasing returns to scale and rapid technical progress.

g =0.03;   #rate of demand growth
delta=0.05; #rate of technical progres
alfa=0.75;   # elasticity of capital
beta=0.75;   # elasticity of labor
r=0.05;   #discout rate

Constant development of prices
Increasing Returns to Scale

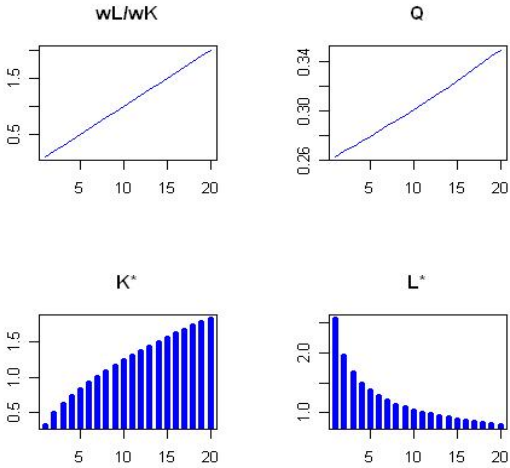| DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	1.00000	1.00000
2	0.99580	1.00000
3	0.99006	1.00000
4	0.98417	1.00000
5	0.97879	1.00000
6	0.97422	1.00000
7	0.97058	1.00000
8	0.96791	1.00000
9	0.96621	1.00000
10	0.96544	1.00000
11	0.96557	1.00000
12	0.96654	1.00000
13	0.96831	1.00000
14	0.97084	1.00000
15	0.97409	1.00000
16	0.97803	1.00000
17	0.98261	1.00000
18	0.98782	1.00000
19	0.99362	1.00000
20	1.00000	1.00000

14
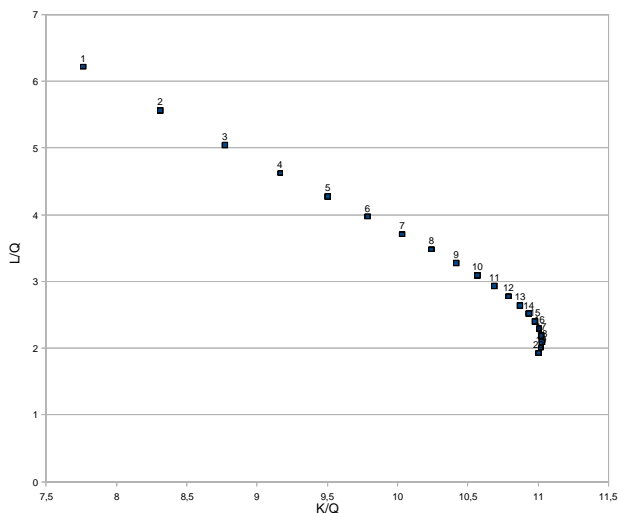
From the input coefficient space it is rather obvious that the first and last vintages are classified as fully efficient in the CRS case. Those are the only units constituting the convex hull of DMUs. Moreover, the efficiency scores decreases from 1 for DMU 1 to 0.965 for DMU 10, then increases up to 1 for DMU 20. In the VRS case all DMUs are classified as fully efficient.

In Case 2, shown in Figure 2, CRS holds, the rate of technical progress is more moderate, 3%, while demand growth is the same as in Case 1, 3%. The efficiency frontier in the CRS case is now more curved towards the origin, so the convex hull is constituted by 13 DMUs and the rest of them are very close to the convex hull. Although there appear very small deviations from full efficiency for all inefficient units, the 13 oldest vintages and the last vintage are fully efficient. Again, in the VRS case all units are fully efficient.

Figure 2: Simulation Case 2 with constant returns to scale and moderate technical progress.

g =0.03;   #rate of demand growth
delta=0.03; #rate of technical progress
alfa=0.4;   # elasticity of capital
beta=0.6;   # elasticity of labor
r=0.05;   #discount rate

Constant prices growth
Constant returns to scale
Higher elasticity with respect to labor

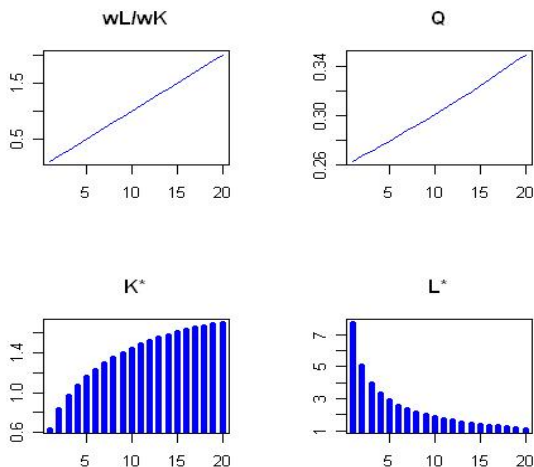| DMU No	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	1.00000	1.00000
2	1.00000	1.00000
3	1.00000	1.00000
4	1.00000	1.00000
5	1.00000	1.00000
6	1.00000	1.00000
7	1.00000	1.00000
8	1.00000	1.00000
9	1.00000	1.00000
10	1.00000	1.00000
11	1.00000	1.00000
12	1.00000	1.00000
13	0.99976	1.00000
14	0.99941	1.00000
15	0.99908	1.00000
16	0.99885	1.00000
17	0.99879	1.00000
18	0.99895	1.00000
19	0.99934	1.00000
20	1.00000	1.00000
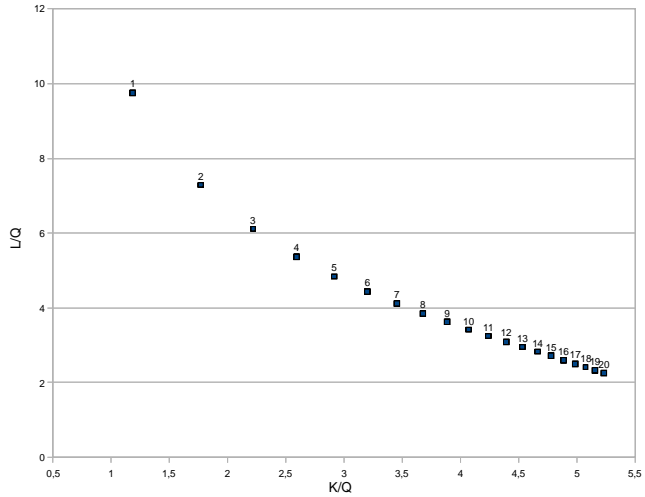
Case 3 shown in Figure 3, is very similar to Case 1, but with slightly higher rate of technical progress i.e., 6%, and with a high marginal elasticity of capital compared to labour. The efficiency frontier in the CRS case is now slightly more curved towards the origin, so the convex hull is constituted by 4 DMUs, the three first vintages and the last. The pattern of efficiency scores is also very similar to Case 1. Although there appear very small deviations from full efficiency for all inefficient units, the 13 oldest vintages and the last vintage are fully efficient. In the VRS case, all but four (16-19) DMUs are on the frontier, although the deviation from the frontier is in the fourth decimal.

Figure 3. Simulation Case 3 with increasing returns to scale and rapid technical progress.

g =0.03;   # rate of demand growth
delta=0.06; # rate of technical progress
alfa=0.9;   # elasticity of capital
beta=0.6;   # elasticity of labor
r=0.05;   # discount rate

Constant rate of prices growth
Increasing Returns to Scale
Higher elasticity with respect to capital
Higher technical progress

DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	1.00000	1.00000
2	1.00000	1.00000
3	1.00000	1.00000
4	0.99420	1.00000
5	0.98454	1.00000
6	0.97513	1.00000
7	0.96724	1.00000
8	0.96121	1.00000
9	0.95704	1.00000
10	0.95463	1.00000
11	0.95383	1.00000
12	0.95450	1.00000
13	0.95650	1.00000
14	0.95972	1.00000
15	0.96406	1.00000
16	0.96943	0.99983
17	0.97577	0.99973
18	0.98301	0.99970
19	0.99110	0.99978
20	1.00000	1.00000
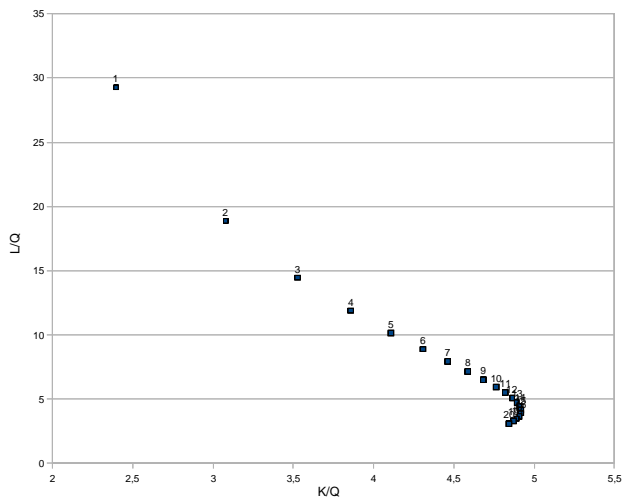
In Case 4, shown in Figure 4, CRS holds, the rate of technical progress is now very rapid, 9%, while demand growth is very slow, 1%. The distribution of DMUs is very similar to Figure 1. From the input coefficient space it is rather obvious that the first and

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last vintages are classified as fully efficient in the CRS case. Those are the only units constituting the convex hull of DMUs. Moreover, the efficiency scores decreases from 1 for DMU 1 to 0.849 for DMU 9, then increases up to 1 for DMU 20.

In the VRS case, however, only the two oldest and the youngest DMUs are fully efficient. As in the CRS case, the efficiency scores decreases from 1 for DMU 2 to 0.886 for DMU 9, then increases up to 1 for DMU 20.

Figure 4. Simulation Case 4 with constant returns to scale, slow demand growth and very rapid technical progress.


```
g =0.01;      # rate of demand growth
delta=0.09;   # rate of technical progress
alfa=0.5;     # elasticity of capital
beta=0.5;     # elasticity of labor
r=0.05;       # discount rate
```

Constant rate of prices growth
Constant elasticity of scale
Very high rate of technical progress
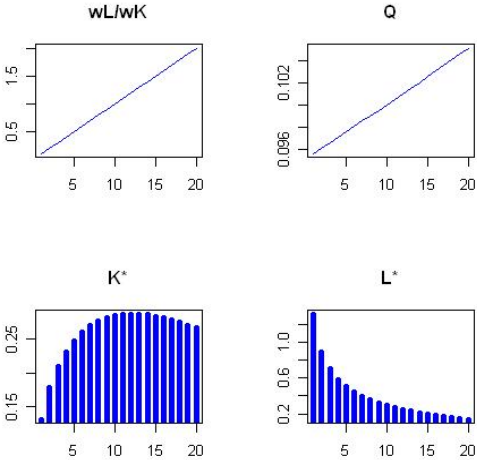
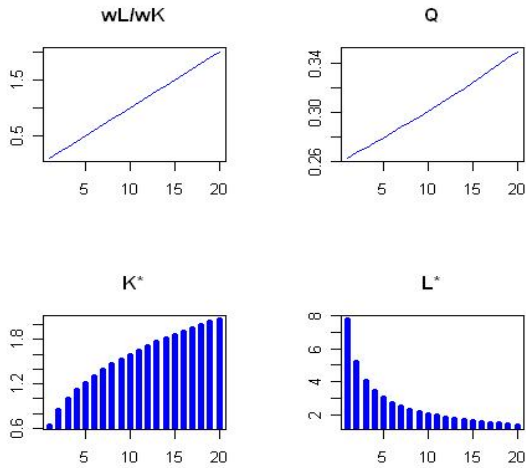| DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	1.00000	1.00000
2	0.97824	1.00000
3	0.93675	0.97165
4	0.90378	0.94389
5	0.88027	0.92205
6	0.86452	0.90618
7	0.85489	0.89544
8	0.85017	0.88902
9	0.84946	0.88621
10	0.85212	0.88648
11	0.85765	0.88941
12	0.86571	0.89468
13	0.87604	0.90203
14	0.88843	0.91128
15	0.90274	0.92226
16	0.91885	0.93487
17	0.93668	0.94901
18	0.95617	0.96461
19	0.97729	0.98162
20	1.00000	1.00000
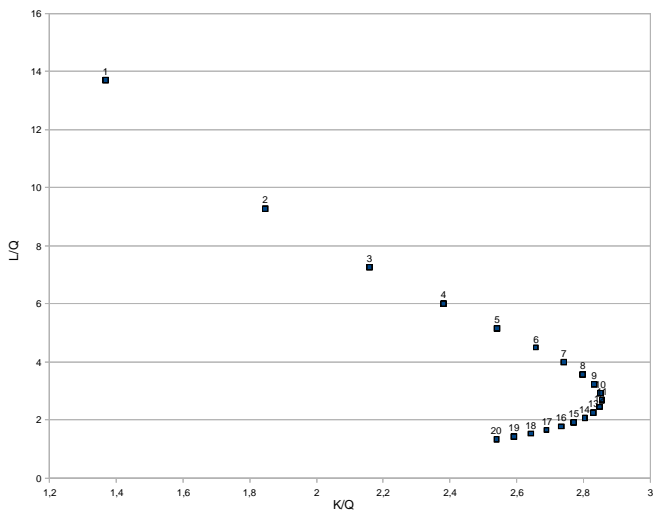
Case 5, shown in Figure 5, with increasing returns to scale, moderate rate of demand and technical progress, and a high capital elasticity, generates an efficiency frontier in the CRS case very similar to Case 2 in Figure 2. The convex hull is constituted by 9 DMUs and the rest of them are very close to the convex hull. Although there appear very small deviations from full efficiency for all inefficient units, the 8 oldest vintages and the last vintage are fully efficient. Again, in the DEA-VRS case all units are fully efficient.

Figure 5. Simulation Case 5 with increasing returns to scale, moderate demand growth, moderate technical progress and high capital elasticity.

g =0.03;   # rate of demand growth
delta=0.03; # rate of technical progres
alfa=0.9;   # elasticity of capital
beta=0.6;   # elasticity of labor
r=0.05;   # discount rate

Constant rate of prices growth
Increasing Returns to Scale
Higher elasticity with respect to capital

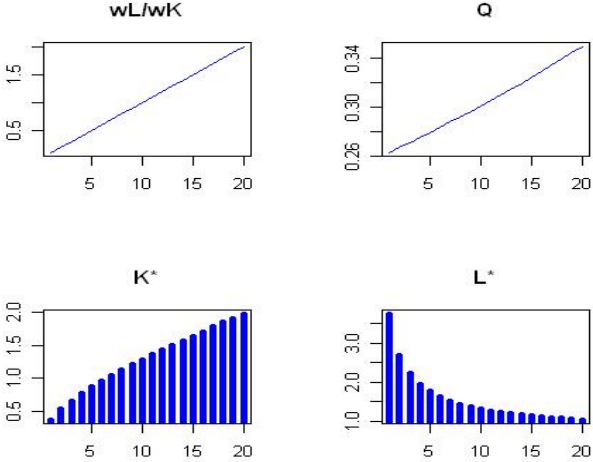| | Input-Oriented CRS | Input-Oriented VRS |
DMU No.	Efficiency	Efficiency
1	1.00000	1.00000
2	1.00000	1.00000
3	1.00000	1.00000
4	1.00000	1.00000
5	1.00000	1.00000
6	1.00000	1.00000
7	1.00000	1.00000
8	1.00000	1.00000
9	0.99901	1.00000
10	0.99763	1.00000
11	0.99623	1.00000
12	0.99503	1.00000
13	0.99415	1.00000
14	0.99367	1.00000
15	0.99362	1.00000
16	0.99401	1.00000
17	0.99485	1.00000
18	0.99614	1.00000
19	0.99786	1.00000
20	1.00000	1.00000
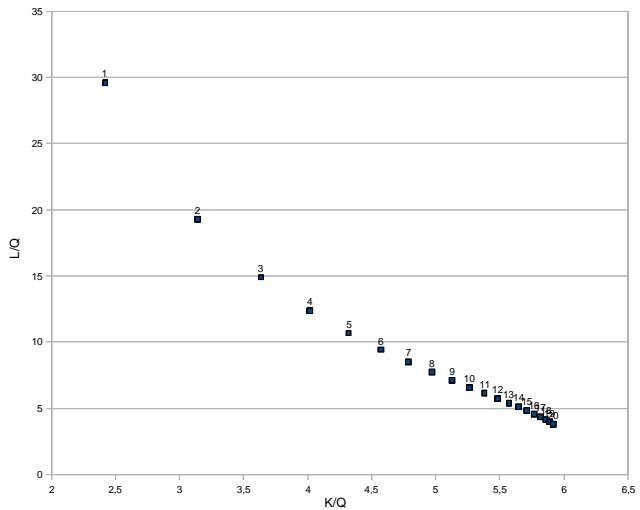
The following is the most extreme case with constant development of input prices. In Case 6, in Figure 6, with constant returns to scale, moderate demand growth

20

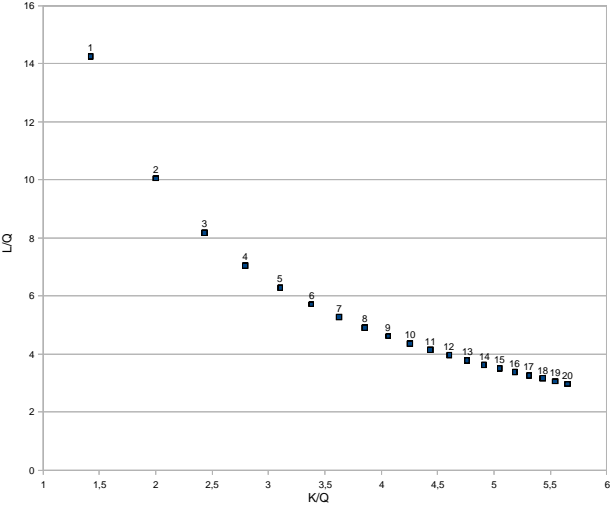and slow technical progress, all DMUs are fully efficient, both in DEA-CRS and DEA-VRS.

Figure 6. Simulation Case 6 with constant returns to scale, moderate demand growth and slow technical progress.

g =0.03; rate of demand growth
delta=0.01; rate of technical prog
alfa=0.5; # elasticity of capital
beta=0.5; # elasticity of labor
r=0.05; # discount rate

Constant development of prices
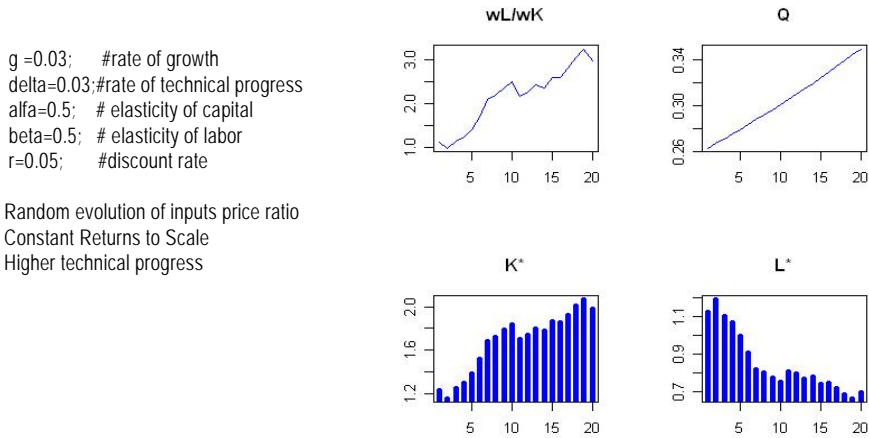Constant Returns to Scale
Smaller technical progress

|	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
DMU No		
1	1.00000	1.00000
2	1.00000	1.00000
3	1.00000	1.00000
4	1.00000	1.00000
5	1.00000	1.00000
6	1.00000	1.00000
7	1.00000	1.00000
8	1.00000	1.00000
9	1.00000	1.00000
10	1.00000	1.00000
11	1.00000	1.00000
12	1.00000	1.00000
13	1.00000	1.00000
14	1.00000	1.00000
15	1.00000	1.00000
16	1.00000	1.00000
17	1.00000	1.00000
18	1.00000	1.00000
19	1.00000	1.00000
20	1.00000	1.00000

Let us also consider a few cases with more heterogeneous input price expectations. Case 7, shown in Figure 7, with constant returns to scale, moderate rate of demand and technical progress, generates a mixed pattern with three units on the convex hull and no clear ranking of units in DEA-CRS, while all units are fully efficient in the DEA-VRS case.

Figure 7. Simulation Case 7 with constant returns to scale, moderate demand growth and moderate technical progress.
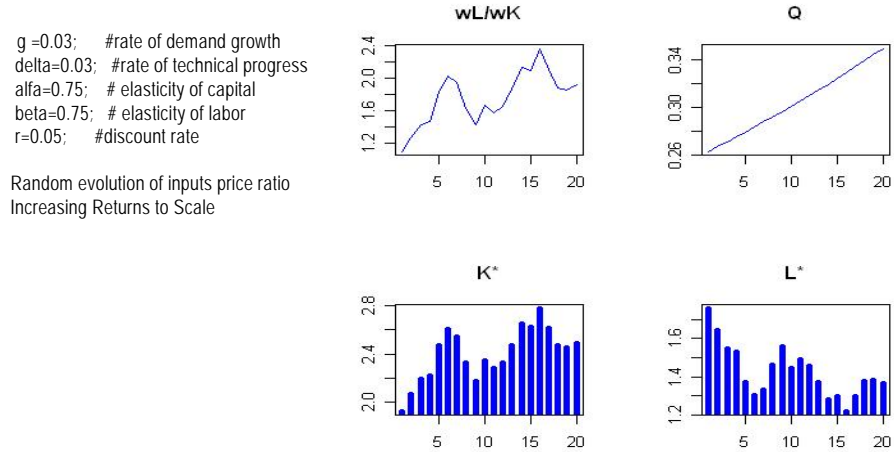
g =0.03;   #rate of growth
delta=0.03;#rate of technical progress
alfa=0.5; # elasticity of capital
beta=0.5; # elasticity of labor
r=0.05;   #discount rate

Random evolution of inputs price ratio
Constant Returns to Scale
Higher technical progress

| DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	0.96631	1.00000
2	1.00000	1.00000
3	0.98979	1.00000
4	0.99223	1.00000
5	0.97944	1.00000
6	0.95173	1.00000
7	0.91310	1.00000
8	0.91545	1.00000
9	0.90816	1.00000
10	0.90590	1.00000
11	0.96152	1.00000
12	0.96584	1.00000
13	0.95922	1.00000
14	0.98185	1.00000
15	0.96703	1.00000
16	0.98465	1.00000
17	0.97456	1.00000
18	0.97548	1.00000
19	1.00000	1.00000
20	1.00000	1.00000
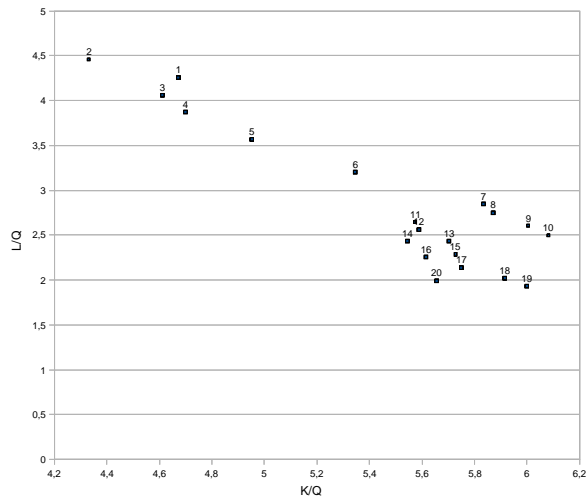
With the same moderate demand growth and technical progress but increasing returns to scale, Figure 8 shows a very diverse pattern. (Note that the abscissa axis is truncated so it is not possible to identify the convex hull.) Here only two DMUs (16 and 20) are on the DEA-CRS frontier while all DMUs are fully efficient in the DEA-VRS case.

Figure 8. Simulation Case 8 with increasing returns to scale, moderate demand growth and moderate technical progress.

g =0.03;   #rate of demand growth
delta=0.03; #rate of technical progress
alfa=0.75;   # elasticity of capital
beta=0.75;   # elasticity of labor
r=0.05;   #discount rate

Random evolution of inputs price ratio
Increasing Returns to Scale

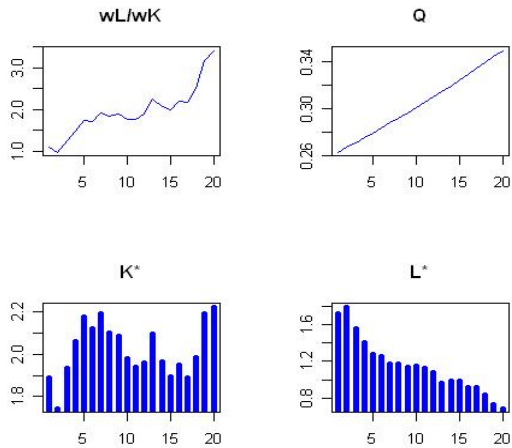| DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	0.96934	1.00000
2	0.91893	1.00000
3	0.87980	1.00000
4	0.88047	1.00000
5	0.80349	1.00000
6	0.83231	1.00000
7	0.83357	1.00000
8	0.89366	1.00000
9	0.96782	1.00000
10	0.91111	1.00000
11	0.95274	1.00000
12	0.94625	1.00000
13	0.90517	1.00000
14	0.94662	1.00000
15	0.95525	1.00000
16	1.00000	1.00000
17	0.98348	1.00000
18	0.97836	1.00000
19	0.99980	1.00000
20	1.00000	1.00000
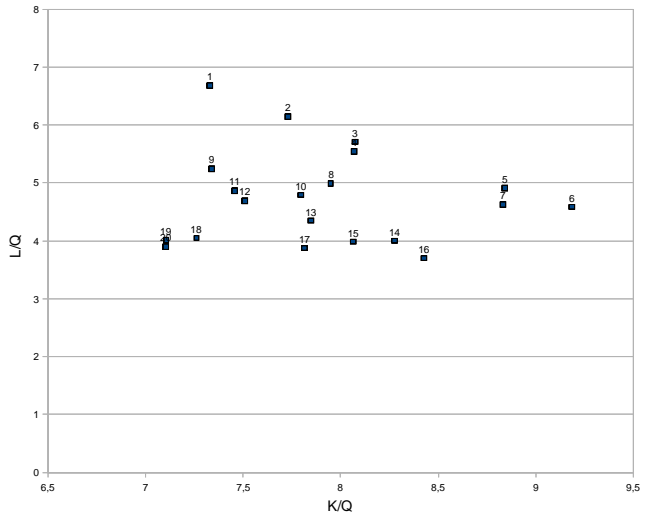
An even more diverse pattern is generated in Case9, Figure 9, with very rapid technical progress. In the DEA-CRS case, three DMUs (17, 18 and 20) are fully efficient, while the least efficient unit is No 7. DEA-VRS also shows a mixed pattern with only four (2, 17, 18 and 20) fully efficient units.

Figure 9. Simulation Case 9 with increasing returns to scale, moderate demand growth and very rapid technical progress.

```
g =0.03;     #rate of demand growth
delta=0.09;  #rate of technical progress
alfa=0.75;   # elasticity of capital
beta=0.75;   # elasticity of labor
r=0.05;      #discout rate

Random  prices but much faster
technical progress than demand growth
```
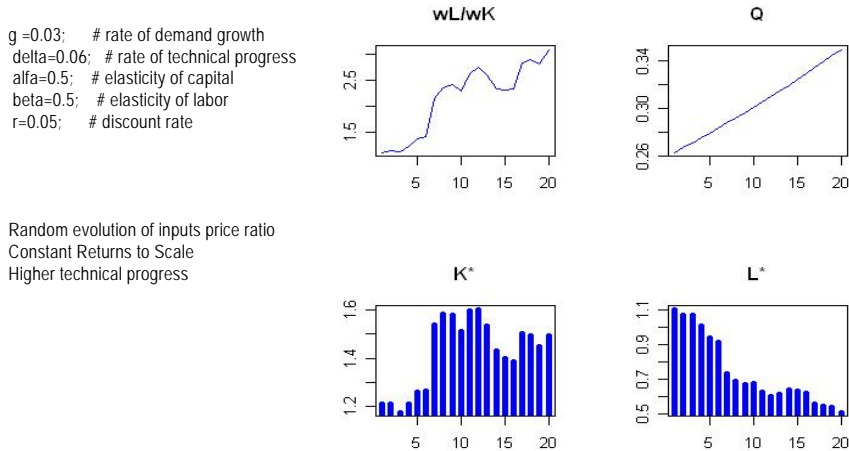
| DMU No	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	0.78649	0.93794
2	0.86563	1.00000
3	0.79245	0.93145
4	0.75515	0.89042
5	0.72569	0.85496
6	0.75522	0.87575
7	0.74176	0.85501
8	0.78514	0.88832
9	0.80444	0.89821
10	0.85872	0.93970
11	0.89050	0.95974
12	0.89591	0.95590
13	0.85942	0.91731
14	0.91904	0.95838
15	0.96977	0.99332
16	0.96093	0.97762
17	1.00000	1.00000
18	1.00000	1.00000
19	0.98222	0.99077
20	1.00000	1.00000
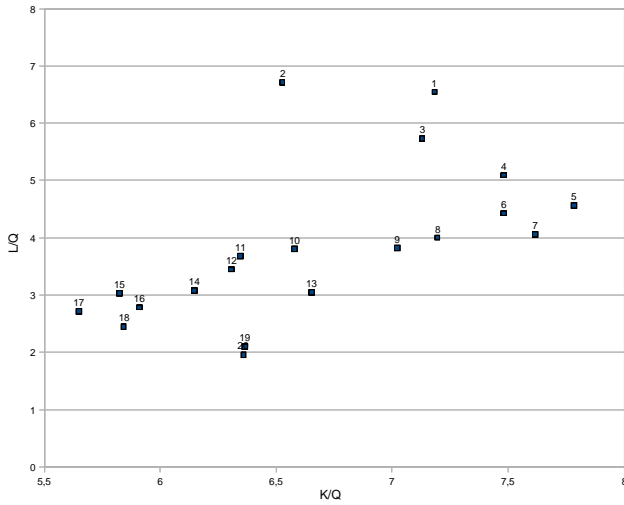
A similar pattern is shown in Figure 10, with constant returns to scale and a rather rapid technical progress. In the DEA-CRS case, the same three DMUs (17, 18 and 20) as in Case 9, are fully efficient, while again the least efficient unit is No 7. DEA-VRS also shows a similar pattern with the same four (2, 17, 18 and 20) fully efficient units.

Figure 10. Simulation Case 10 with constant returns to scale, moderate demand growth and rather rapid technical progress.

g =0.03;   # rate of demand growth
delta=0.06; # rate of technical progress
alfa=0.5;   # elasticity of capital
beta=0.5;   # elasticity of labor
r=0.05;   # discount rate

Random evolution of inputs price ratio
Constant Returns to Scale
Higher technical progress

DMU No.	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency
1	0.91186	0.97231
2	0.92520	0.97949
3	0.96639	1.00000
4	0.95469	0.99671
5	0.92899	0.98471
6	0.94260	0.99189
7	0.78632	0.89083
8	0.77663	0.88161
9	0.78993	0.88935
10	0.83658	0.91488
11	0.80644	0.89857
12	0.81444	0.90260
13	0.86416	0.93028
14	0.93958	0.96940
15	0.97294	0.98679
16	1.00000	1.00000
17	0.93822	0.96868
18	0.96169	0.98079
19	1.00000	1.00000
20	1.00000	1.00000
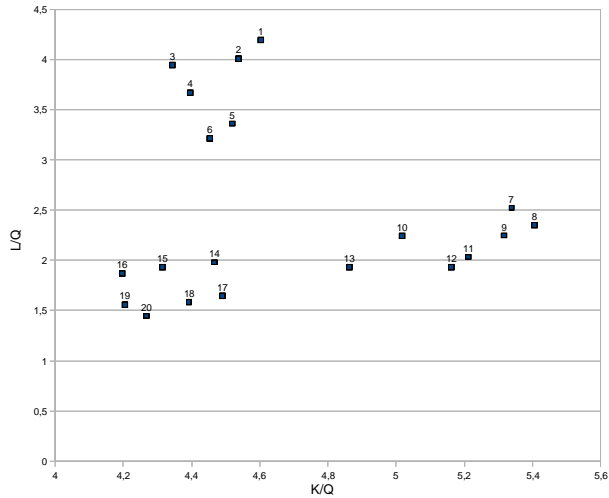
The overall impression of the 10 cases is that the putty-clay capacity expansion model may generate efficiency distributions with rather different features and without any clear link between efficiency structure (as measured by DEA) and vintage structure. Because of its flexibility, the VRS results are, of course, most extreme with very little deviation from the frontier. The CRS results vary more between different parameter combinations, and without a clear pattern.

A priori, one may expect a strong correlation between the vintage of a plant and its efficiency; see Kumbhakar et al. (1997). However, this is not at all the case. The oldest vintage may come out as efficient as the most recent one, even in the case of rapid technical progress, and it is not easy to find any specific pattern behind the generated efficiency distributions in the different cases.

In empirical applications it would, of course, be very rare to find such "smooth" distributions as in Case 1-6. Varying relative price expectations, disembodied technical progress and different learning experience with new technology will generate more variation in the distributions, as in Cases 7-10.

Moreover, in a putty-clay world, plants will be closed down when the quasi-rent is zero, so from a prediction point of view we should expect a phasing out of DMUs

according to the vintage structure. Here we lack that type of mechanism, but it is worth noting that in all Cases 1-6 (but not in Cases 7-10), the oldest vintage has an efficiency score of 1, while in all Cases 1-10, the youngest vintage is at the frontier.

The results generated by the different cases may seem quite amazing. However, DEA is a "convex hull approach" and under certain assumptions all DMUs may be on the frontier in some cases. When capital is substituted for labour over time, a linear programming approach will catch some labour-intensive units as fully efficient just because they lack competition in that area of the input coefficient space. When efficiency is interpreted as a distance measures this makes perfect sense.

When efficiency is given a normative policy interpretation as performance measure, the results may cause some concern. From a normative point of view it does not make sense to regard a 20 year old plant as efficient as a new one in an industry with rapid technical progress. Just to let data talk – or rather measurement without theory – may be a dangerous approach. While a lot of effort has been spent on different approaches to efficiency measurement, very little has been spent on inefficiency generating mechanisms. Without a clear link to the data generating mechanism one should be very cautious when it comes to application of efficiency scores in performance measurement. This holds in particular in an industry characterized by putty-clay and embodied technical progress.

6. Conclusions

In this paper I develop a model of capacity expansion that accounts for differences in the productivity of the installed capital due to technical progress exhibited by the *ex ante* production function. A putty-clay set-up is assumed, meaning flexible input coefficients and substitution possibilities *ex ante*, but fixed input coefficients *ex post*. Based on the model, I generate a capacity distribution of DMUs (vintages) for a homogenous industry and perform an efficiency analysis employing data envelopment analysis, a popular non-parametric method for estimating efficiency. The results show that in some circumstances older vintages appear on the efficiency frontier, unlike some newer vintages that are found to be inefficient, despite benefiting from the advancement

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of the technology. In extreme cases all DMUs might be at the efficiency frontier even in the case of constant returns to scale. The main conclusion from this exercise is that one should be careful about normative interpretations of efficiency differences.

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Appendix 1

When firms expect exponential wage growth, with growth parameter *a*, then:

(1.8) $\quad C_t = w_K(t) \cdot K_t + \sum_{s=t}^{\infty} w_L(s) L_t \cdot e^{-rt}$
.

However, now $w(t) = w_0 \cdot e^{at}, a \geq 0$, where *a* is the rate of wage growth.

Then the cost the firms face is:

(1.9) $\quad C_t = w_K(t) \cdot K_t + L_t \sum_{s=t}^{\infty} w_0 \cdot e^{(a-r)t} = w_K(t) \cdot K_t + w_0 \cdot L_t \dfrac{e^{(a-r)t}}{1 - e^{(a-r)}},$

where *a-r <0 <=> a<r.*

Hence, for the relation above to exist, it is required that the rate of wage growth is always smaller than the discount rate.

Appendix 2

The optimisation programme associated with the investment decision at time t is:

$$\min_{K_t, L_t} C_t = w_K(t) \cdot K_t + \sum_{s=t}^{\infty} w_L(s) \cdot L_t \cdot e^{-rt}$$

such as

(1.10)
$$A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta} = Q_0 \cdot e^{gt}(1 - e^{-g})$$

Since

(1.11)
$$\sum_{s=t}^{\infty} (e^{-r})^s = \frac{e^{-rt}}{1 - e^{-r}}$$

and

(1.12)
$$w_L(s) = w_L(t), \text{for } s > t$$,

the optimisation programme becomes:

$$\min_{K_t, L_t} C_t = w_K(t) \cdot K_t + w_L(t) \cdot L_t \cdot \frac{e^{-rt}}{1 - e^{-r}}$$

such as

(1.13)
$$A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta} = Q_0 \cdot e^{gt}(1 - e^{-g})$$

First-order conditions for optimality imply:[9]

(1.14)
$$w_K(t) = \alpha \cdot A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha-1} \cdot L_t^{\beta}$$

(1.15)
$$w_L(t) \cdot \frac{e^{-rt}}{1 - e^{-r}} = \beta \cdot A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta-1}$$

(1.16)
$$A_0 \cdot e^{\delta \cdot t} \cdot K_t^{\alpha} \cdot L_t^{\beta} = Q_0 \cdot e^{gt}(1 - e^{-g})$$.

Following this we can write:

---

[9] The concavity of the objective function ensures the uniqueness of the optimal solution.

(1.17)
$$\frac{w_K(t)}{w_L(t)} \cdot \frac{1-e^{-r}}{e^{-rt}} = \frac{\alpha}{\beta} \cdot \frac{L_t}{K_t}.$$

Substituting L_t with $\dfrac{w_K(t)}{w_L(t)} \cdot \dfrac{1-e^{-r}}{e^{-rt}} \cdot \dfrac{\beta}{\alpha} \cdot K_t$, it follows that:

(1.18)
$$K_t^{\alpha+\beta} = \frac{Q_0}{A_0} \cdot e^{(g-\delta-r\beta)\cdot t} \cdot \left(\frac{\alpha}{\beta} \cdot \frac{w_L(t)}{w_K(t)}\right)^{\beta} \cdot \frac{(1-e^{-g})}{(1-e^{-r})^{\beta}}.$$

Hence, the optimal instalment will be:

(1.19)
$$K_t^* = \left(\frac{Q_0}{A_0}\right)^{1/\varepsilon} \cdot e^{(\frac{g-\delta-r\beta}{\varepsilon})\cdot t} \cdot \left(\frac{\alpha}{\beta} \cdot \frac{w_L(t)}{w_K(t)}\right)^{\beta/\varepsilon} \cdot \frac{(1-e^{-g})^{1/\varepsilon}}{(1-e^{-r})^{\beta/\varepsilon}}, \text{ where } \varepsilon = \alpha+\beta.$$

Similarly:

(1.20)
$$L_t^* = \left(\frac{Q_0}{A_0}\right)^{1/\varepsilon} \cdot e^{(\frac{g-\delta-r\alpha}{\varepsilon})\cdot t} \cdot \left(\frac{\beta}{\alpha} \cdot \frac{w_K(t)}{w_L(t)}\right)^{\alpha/\varepsilon} \cdot \frac{(1-e^{-g})^{1/\varepsilon}}{(1-e^{-r})^{\alpha/\varepsilon}}.$$

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