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- the efficiency of Icelandic firms

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Creating Innovations, Productivity and Growth

The Efficiency of Icelandic Firms

Dong-hyun Oh ℘ and Hans Lööf ⊗

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Abstract

Iceland is one of the smallest European economies and the country was hit severely by the 2008-financial crisis. This paper considers the economy in the period preceding the collapse. Applying a Data Envelopment Analysis on 204 randomly selected firms, the results suggest that a substantial fraction of the Icelandic firms can be classified as non-efficient in their production process. The production scale of many manufacturing firms is too small to be technically efficient, while service firms typically use excessive resources in their production process. A remarkably weak performance in transforming R&D and labour efforts into successful innovations is observed.

Keywords: Technical efficiency, R&D, Innovation, Productivity

JEL-codes: C14, D24, L6, L8, O14, O33

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1. Introduction

Iceland is one of the smallest European economies with only about 170,000 employees. The country has been considered as a politically stable Scandinavian-type economy with high standard of living,[3] low unemployment, even distribution of income, advanced health care and a well-functioning education system. The major trade partners are other Northern-European countries and the U.S. The economy depends heavily on the fishing industry which has been diversified into growing manufacturing and service industries. Recently branches such as financial services, software, biotechnology and tourism have shown a strong development.

After the collapse of Iceland's financial system in early autumn 2008 the Icelandic krona was depreciated with about 50 %, the economy contracted sharply, real wages fell about 15 % and the unemployment started to grow rapidly.

This paper considers the Icelandic economy a couple of years before the collapse and it tries to make a diagnosis of the competitiveness of manufacturing and service industries. The analysis makes use of 204 randomly selected firm level observations for the period 2004-2006. The first two years of this period are characterized by a strong economic boom with annual growth rates above 6 %, followed by a mini-crisis in 2006 with a growth rate just over 1 %.

The main idea of the study is to explore how efficient the Icelandic Economy used its basic labour and R&D resources during a period which was extreme in several respect: the economy was over-heated with a negligible unemployment rate and a large and growing number of non-resident work force of Icelandic companies, the total assets of the banking sector increased to

[3] Per capita GDP was $ 40 000 (PPP) in year 2007 corresponding to 6th in OECD (World Bank)

800% of GDP in 2006 (from under 100% in 2000), the countries net external debt increased from just over 100% of GDP in 2004 to over 200% in 2006 and the inflation rate increased from 2 to 7 % between 2003 and 2006 (the target rate for the Iceland Central bank, ICB is 1,5%).

The hypothesis to be investigated is that overall conditions for innovativeness, efficiency and productivity was weak in the booming and over-heated economy with its independent monetary policy, floating exchange and inflation rate. The latter can be interpreted as absence of strong external pressure on a disciplinary economic policy.

A common empirical approach for analyzing relationships between R&D, innovation, productivity and growth is parametric model of a Cobb-Douglas form. A growing number of these studies are using the same kind firm-level data set as the present paper, namely those from the Community Innovation Survey (CIS). The internationally harmonized CIS-data is containing a rich variety of information on innovative activities, firm characteristics and economic performance.

A small strand of the literature is using nonparametric estimators for analyzing the CIS-data. Two options are Stochastic frontier analysis (SFA) and Data envelopment analysis (DEA). While the former is appropriate for single output studies, the DEA is designed to handle multi outputs cases, which are considered in the present paper.

Methodologically, DEA employs linear programming to estimate the best-practice frontier and the performance of decision making units (DMUs). In this study DMUs are Icelandic firms. Data envelopment analysis is regarded as a counterpart of the parametric estimation approaches in the sense that it does not require any assumptions on the underlying functional form of production activities and it is free from the distributional assumption of the error term. In addition DEA can deal with multi-inputs and multi-outputs bundles of production process.

However, despite several desirable properties in the DEA-approach, problems regarding strong assumptions on homogenous production processes may arise. Parametric studies are partly solving this problem by allowing for heterogeneity between sectors by inclusions of industry dummies and between observations by taking unobservable firms specific fixed effects into account. In this paper, the issue of heterogeneity is highlighted in some sensitivity tests.

In DEA the efficiency of each DMU can be estimated by means of n optimization problems (where n is number of DMUs) by constructing the best-practice frontiers with observed inputs-outputs bundles of the DMUs. Contrary to the single optimization problem of the traditional parametric statistical approaches, DEA is regarded as a DMU-specific optimization approach. The authors of this paper believe that DEA can be appropriately modified to test the hypothesis proposed. In order to do so, they employ both the conventional DEA models and the imprecise DEA models (IDEA). With the latter model binary variables can be included in the model specification. The present paper makes use a simplified version (Zhu, 2004) of the original IDEA model.

DEA has been widely exploited in different industrial sectors in the field of industrial economics and management, in which performance evaluation and benchmarking studies are mainly considered. Zhu (2000) employs DEA to examine the multi-dimensional financial performance of Fortune 500 companies; Tsai et al. (2006) analyzed the performance of 29 leading Forbes 2000 telecom operators; Yang (2006) explored the efficiency of fund-receiving enterprises in Korea over the period 2000-2002. One of the few DEA-studies that is close to the general framework of this study is Castellacci and Cheng (2008) which uses Norwegian CIS data in order to investigate the relationship between different Schumpeterian patterns of innovation and firm level productivity.[4]

This paper contributes to the literature that exploits the CIS-data for studies on R&D, innovation, productivity and growth in a non-parametric framework. Using DEA the following main findings emerge from the present study. First, about 90 % of the Icelandic firms can be classified as non-efficient in the process of transforming labour and R&D efforts into to output in terms of innovations, productivity and growth. Second, the manufacturing sector as a whole has somewhat higher technical efficiency than service sector, while the latter has the higher scale efficiency. This implies that adjusting the size of firm is a better strategy for increasing efficiency among the firms in the Icelandic manufacturing sector, while reducing unnecessary resources is a more optimal strategy for the services. Third, the Icelandic firms have a low rate of return on R&D. The lack of efficiency is suggested to be a combined effect of the smallness of the market for many Icelandic firms and an overheated economy.

The remaining parts of this paper are organized as follows: Section 2 briefly introduces the DEA methodologies. Section 3 presents the data. In Section 4 the results are presented followed by a concluding discussion in Section 5.

2. Empirical Models

[4] A selected number of studies on technical efficiency at the firm level are reported in Appendix, Table A1.

This section presents a brief introduction of technical efficiency. A more detailed model with mathematical notations is provided in Appendix A.2.

Data envelopment analysis, DEA, is a method for measuring comparative or relative efficiency as a proxy of performance of decision making units, DMUs. In the present paper DMUs are Icelandic firms. In DEA the resources are typically referred to as “inputs” and the outcomes as “outputs”, and a DMU transforms inputs into outputs in a production process (Thanassoulis, 2001).

The main objective of DEA is (i) to measure how much inputs can be reduced for at most a given value of outputs when the production process is technically efficient, or (ii) to measure how much outputs are increased for at least a given value of inputs when the production process is technically efficient. The former measure is referred to as the input-oriented measure and the latter is referred to as the output-oriented measure.

In order to measure the potential contraction of inputs or the potential expansion of outputs, particular forms of returns-to-scale need to be assumed in constructing a *production possibility set* (PPS). The assumptions are a constant returns-to-scale (CRS) or a variable returns-to-scale (VRS). In the latter assumption of returns-to-scale, an increasing, constant and decreasing returns-to-scale are allowed. In the CRS assumption, outputs will increase proportionally to input on the frontier. In the VRS assumptions, on the other hand, the returns to inputs will vary.

Figure 1 illustrates the CRS and VRS production possibility sets with a single output and a single input. The horizontal axis represents input, and the vertical axis represents output. Below the thick solid line from the origin is the PPS under the CRS assumption, and below the piecewise linear thick solid line is the PPS under the VRS assumption. We now consider how the technical efficiency of DMU A is measured. The input-oriented technical efficiency under CRS is measured as CD/AD and the input-oriented technical efficiency under VRS is measured as BD/AD. Hence, the input-oriented technical efficiency is regarded as the measure of potential reduction of input. The output-oriented technical efficiency under CRS is measured as DF/DA and the output-oriented technical efficiency under VRS is measured as DE/DA. Thus, the output-oriented technical efficiency measures potential expansion of an output with a given input.

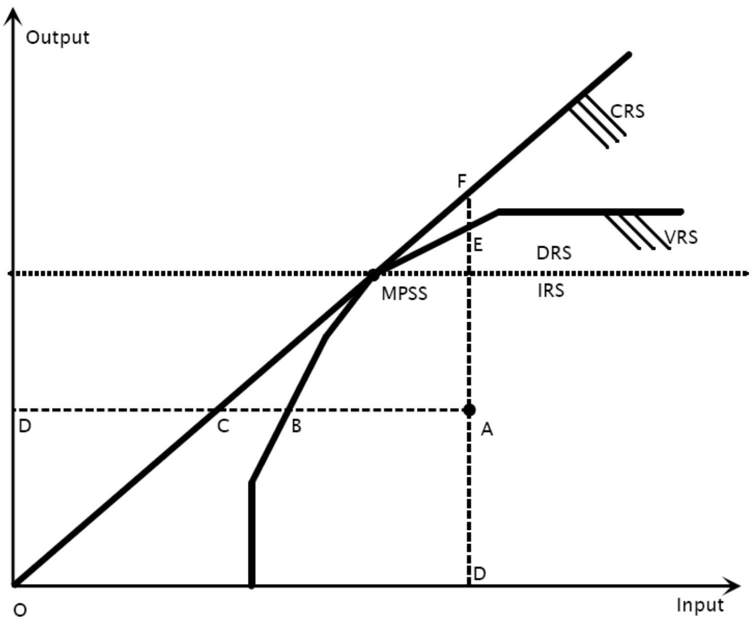


Figure 1. CRS and VRS production possibility sets and technical efficiency.

The ratio of CRS efficiency to VRS efficiency is defined as scale efficiency. The larger ratio between CRS and VRS, the closer a DMU is operating to the so called *Most Productive Scale Size (MPSS)* (Thanassoulis 2001). On MPSS, the DMUs will exhibit the maximum average productivity. Scale efficiency of DMU *A* with respect to the *input-oriented measure* is CD / BD and the scale efficiency of DMU *A* with respect to *output-oriented measure* is DF / DE. Hence, the scale efficiency shows how far a DMU is located from the MPSS. When a DMU is operating below the MPSS, then the DMU is operating in the increasing returns-to-scale region (IRS). When a DMU is operating upper the MPSS, then the DMU is operating in the decreasing returns-to-scale region (DRS). In the increasing returns-to-scale region, increasing the size of DMU will increase the average productivity. In the decreasing returns-to-scale region, decreasing the size of DMU will increase the productivity.

Figure 2 provides an illustration of a two inputs case.

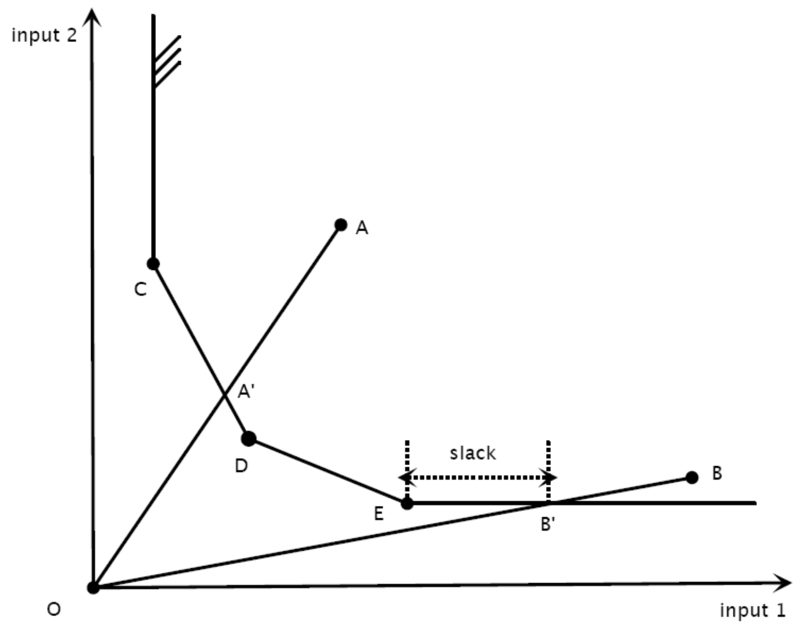


Figure 2: Production possibility set in a two inputs case: five decision making units, or firms. Piecewise linear solid line represents the best practice frontier.

In the figure, it is assumed that each one of five different DMUs produces a single unit of output with a mix of two inputs. For instance, DMU *A* is producing one unit of output with an input bundle given as the point A. The DMUs *C, D* and *E* construct the technology frontier, and the technical inefficiency is measured relatively to this frontier.

The input-oriented technical inefficiency of DMU *A* is measured as the distance from the point A to the point A', which yields the input-oriented technical efficiency measure as OA'/OA. The input-oriented technical efficiencies of the three decision making units *C, D* and *E* are unity since they are on the frontier. Thus, the input-oriented technical efficiency also can be seen as the ratio of 'the distance from the origin to the point on the frontier toward the given point' to 'the distance form the origin to the given point'.

The output-oriented technical efficiency is analogous to the input-oriented measure. However, since we only deal with the input-oriented measure in this study the output-oriented technical efficiency will not be discussed any further (interested readers can be referred to Cooper et al. 2000). If the technical efficiency of a DMU is equal to unity, then we say that the DMU is technically efficient. If the technical efficiency of a DMU is less than unity, then we say that the DMU is technically inefficient (or equivalently, the DMU is not technically efficient)

It should be noted that it is possible for a DMU to continue to improve its production process even after its inputs are proportionally reduced till it reaches the frontier. Consider DMU *B* in Figure 2. A proportional decrease of its input bundle moves from B to B'. However, the firm can still be on the frontier after reducing the Input 1 further by the amount of EB'. Now it uses the same amount of Input 2 as previous but less of input 1, resulting in better performance. The difference between the initial position on the technology frontier (B') and the new and more efficient position (E) is labeled as *slack*. In the presence of slack (excessive use of Input 1 in this example), the firm *B* in Figure 2 fails to be in the so called *Pareto optimal region*. In the Pareto optimal region no additional output can be produced without additional inputs. In this region production plans are called “well-harmonized”. Hence, an elimination of input slacks means that a DMU is moving towards the Pareto optimal region. The analogous discussion can be given in the output space, which gives output slacks.

The Community Innovation Survey includes categorical variables on various firm characteristics. A drawback with the conventional DEA model is that it cannot properly deal with such information. In order to consider these variables in our empirical analysis, we also employ an *imprecise DEA* (IDEA). When we consider only the continuous variables we employed the conventional DEA, and when we consider both of the dummy variables and continuous variables we employed the IDEA. IDEA was first introduced by Kim et al. (1999) and we apply the model proposed by Zhu (2004) in which a calculation process is extensively simplified compared with the original approach. Due to the fact that the VRS for IDEA has not been developed yet, we only employ the CRS IDEA model in our empirical study.

3. Data description

The analysis makes use of 204 observations on Icelandic firms in manufacturing and service industries and utility for the period 2004-2006. Economic variables such as sales and number of employees are reported 2004 and 2006, while variables on innovation activities are reported only for year 2006. Missing values in the sample has been replaced by imputed values.

Table 1. Summary statistics, key variables in the study. The economic variables are expressed in thousand/ million Icelandic Kronas.

1.	2. Mean	3. Std dev	4. Median
5. Output	6.	7.	8.
9. Sales growth, annually	10. 22.4 %	11. 141.0%	12. 6.7 %
13. Productivity, log	14. 9.44	15. 0.91	16. 9.31
17. Innovation sales, log	18. 7.69	19. 1.43	20. 7.71
21. Input	22.	23.	24.
25. Employment	26. 60	27. 116	28. 26
29. Employment, log	30. 3.46	31. 0.96	32. 3.37
33. Total R&D, log	34. 8.76	35. 2.93	36. 9.60
37. Product innovation, dummy	38. 0.47	39. 0.5	40. 0.00
41. Process innovation, dummy	42. 0.26	43. 0.44	44. 0.00
45. R&D support, dummy	46. 0.39	47. 0.49	48. 0.00
49. IPR, dummy	50. 0.18	51. 0.38	52. 0.00

Three different output measures are used in the study. The first is annual sales growth 2004-2006. The summary statistics presented in Table 1 shows that the distribution is highly skewed to the right, which indicates that some of firms have a considerably larger growth rate compared to the majority of firms. This is reflected in the large gap between mean value (22%) and median (7%). The second output measure is sales per employee, or gross productivity. As could be expected, Table 1 reports that the mean value is somewhat larger than the median reflecting that some firms in the sample are very high productive. The final output is innovation sales. It is defined as sales income year 2006 from new products (product innovations) launched on the market during the period 2004-2006. Innovation sales is expressed in per employee terms.

Looking then at the input variables in the bottom of Table 1, we see that the average number of employees is 60 while the median firm has only 29 employees. The minimum number of employees in the sample is 10.

One out of four Icelandic firms in the sample is conducting process innovations, while 47 % are product innovators. The vast majority of firms engaged in product innovation also report process innovation activities. The fraction of firms engaged in either process or product innovations, or in both, is close to 50 %.

The R&D expenditures for the typical firm in the sample correspond to about 2 % of sales. Note that Table 1 reports that the log of R&D expenditures is lower for the mean firm compared to median firm. This puzzling finding is explained by the conventional methodology of replacing the zero in R&D expenditures for non-R&D firms with a small positive amount before taking the logs.

The bottom rows of Table 1 report that 39 % of the Icelandic firm received R&D support from the government or from the EU, and that 18% of firms used the legal system for intellectual property rights in

4. Results

In this section we report the results of the analyses for the conventional data envelopment analysis (DEA) and the imprecise data envelopment analysis (IDEA). An intuitive description of the methodology is provided in Section 2 and a detailed discussion is presented in Appendix A.2.

Returns-to-scale is the basic assumption for measuring the technical efficiency, which constructs a production possibility set from the observations. The main focus is on the technical efficiencies under the constant returns-to-scale (CRS) and variable returns-to-scale (VRS), both of which express how efficiently the firms are using their resources. In contrast to the CRS assumption (only constant returns is allowed), the VRS assumption allows increasing, decreasing and constant returns-to-scale. We will also report results on scale efficiency, decreasing returns to scale, increasing returns to scale and results from the slack analysis.

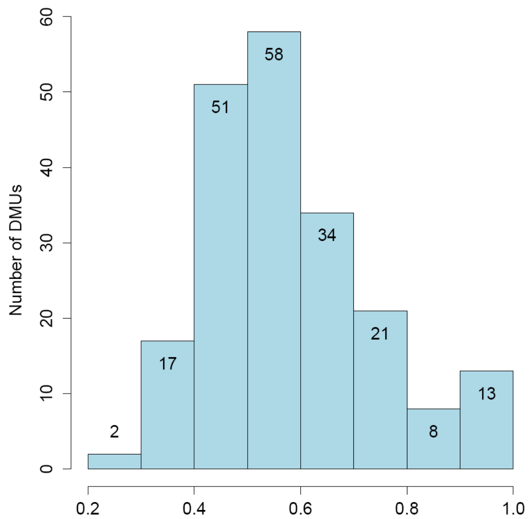
In the CRS assumption, production plans on the frontier will increase output proportionally to inputs. In the VRS assumptions, on the other hand, the returns to inputs will vary. In the increasing (decreasing) returns-to-scale region, an increase (a decrease) of the scale will increase the average productivity. The point which represents the average maximal productivity is referred to as Most Productivity Scale Size (MPSS). The scale efficiency measures how far a DMU is operating from the MPSS. The slack of input (output) is the amount of input (output) which can be further decreased (increased) after the proportional decreasing of inputs. A production plan without slacks is referred to as being well-harmonized.

In the more commonly used parametric models and a partial derivative framework, the elasticity of output is estimated with respect to input variables and various covariates. DEA and IDEA, however, express relationships between a set of multi outputs and a set of multi input factors within the assumption of the production possibility set. In the present paper outputs are sales growth, labour productivity and income per employees from new products. The input variables in DEA are labour and R&D expenditure per employee. Using the IDEA, we will add three categorical variables to the input factors: process innovation, public R&D support and intellectual property rights.

4.1 Technical efficiency using DEA

We start by presenting the results from the conventional DEA. Figure 3 shows the distributions of the CRS and VRS technical efficiency scores. The range of the score is between 0 and 1. The left panel of Figure 3 displays the distribution of the CRS scores. It can be seen that only 6% (13 out of 204) of the firms achieve CRS efficiency with a score equal to or close to 1. About 85% of the firms have CRS score within the range of 0.40- 0.95, and 9% of them have the CRS scores below 0.4.

Our initial conclusion is that the vast majority of the Icelandic firms can be considered as non-efficient. They are using excessive resources of R&D and labour when producing their products and services. An alternative way of interpreting the results is that these firms could switch to the best practice production technology; they have a potential to improve their production process and they can produce the present level of output with less resources.



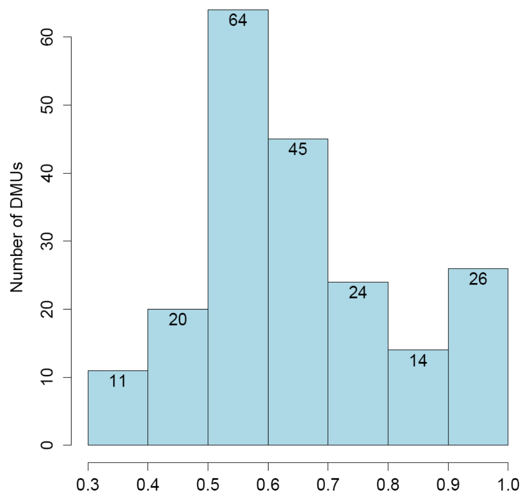


Figure 3. Distribution of technical efficiency.

(a) CRS efficiency distribution (b) VRS efficiency distribution

The right panel of Figure 3 illustrates the distribution of the VRS efficiency score. The panel reports that about 13% of the firms (26 out of 204) are technically efficient. For the rest of the Icelandic firms, the VRS scores are distributed between 0.3 and 0.95. Together, the two efficiency measures produce fairly robust evidence that the firms investigated are not optimizing their production process. About nine out of ten Icelandic firms can be classified as being non-efficient in transforming labour and R&D efforts into outputs in terms of innovations, productivity and growth over the period 2004-2006

Tables 2a and 2b shows the distribution of CRS and VRS efficiency scores decomposed on 14 different manufacturing and service industries in Iceland. All the industries have the average CRS efficiency between 0.50 and 0.66 and the average VRS efficiency between 0.57 and 0.75.

Table 2a. DEA results for manufacturing industries

53.	54. (1)	55. (2)	56. (3)	57. (4)	58. (5)	59. (6)	60. (7)
61.	62. Number of firms	63. CRS	64. VRS	65. Scale effic.	66. DRS 67. (%)	68. IRS 69. (%)	70. MPSS 71. (%)
72. Wood and paper products	73. 19	74. 0.654	75. 0.754	76. 0.872	77. 0	78. 100	79. 0
80. Chemicals	81. 19	82. 0.625	83. 0.724	84. 0.857	85. 0	86. 94.7	87. 5.3
88. Transport equipment	89. 19	90. 0.609	91. 0.697	92. 0.876	93. 0	94. 100	95. 0
96. Apparel and leather products	97. 33	98. 0.559	99. 0.620	100. 0.903	101. 0	102. 97	103. 3.0
104. Metal products	105. 10	106. 0.529	107. 0.604	108. 0.879	109. 0	110. 100	111. 0
112. Electronics and electrical equipment	113. 9	114. 0.519	115. 0.563	116. 0.927	117. 0	118. 100	119. 0
120. Other products	121. 4	122. 0.505	123. 0.573	124. 0.885	125. 0	126. 100	127. 0
128. Manufacturing total	**129. 113**	**130. 0.587**	**131. 0.665**	**132. 0.885**	**133. 0**	**134. 98.2**	**135. 1.8**

Starting with the manufacturing industry, the efficiency results reported in Table 2a indicate a large heterogeneity among different branches. Wood and paper products, and chemical products are considerably more efficient than metal products, electronics and electrical products and other products in the bottom. Transport equipment and apparel and leather have an intermediate position. The pattern is similar whether we consider the CRS or VRS technical efficiency in the two first columns.

We now consider the four last columns of the table. In column 4, the results for scale efficiency are presented. Columns 5 and 6 reports presence of decreasing or increasing returns to scale and the last column shows the MPSS-results. Scale efficiency measures the gap between the CRS and VRS technical efficiencies. By definition, a large value of the scale efficiency corresponds to a small gap between the two efficiency measures and shows how far the firm is located from the Most Productivity Scale Size (MPSS). As the name of this measure indicates indicates, a production plan in the MPSS yield the maximal productivity.

If a firm is operating in the DRS (IRS) region, the firm needs to decrease (increase) their size to reach the MPSS. As can be seen in column 7, most firms do not operate on the MPSS regions and column 6 reports that around 98% of the firms need to increase their size to maximize their productivity. This fact signifies that the size of the Icelandic firms is not large enough to maximize their productivity. Only 2% of the firms are operating on their optimal scale.

Table 2b. DEA results for service industries

136.	137. (1)	138. (2)	139. (3)	140. (4)	141. (5)	142. (6)	143. (7)
144.	145. Number of firms	146. CRS	147. VRS	148. Scale effic.	149. DRS 150. (%)	151. IRS 152. (%)	153. MPSS 154. (%)
155. Financial and insurance activities	156. 16	157. 0.618	158. 0.665	159. 0.929	160. 12.5	161. 75	162. 12.5
163. Transport and storage	164. 16	165. 0.608	166. 0.628	167. 0.965	168. 12.5	169. 81.2	170. 6.3
171. Water supply	172. 6	173. 0.594	174. 0.666	175. 0.891	176. 0	177. 100	178. 0
179. Scientific and Technical activities	180. 25	181. 0.570	182. 0.648	183. 0.882	184. 0	185. 96	186. 4
187. Construction	188. 3	189. 0.556	190. 0.581	191. 0.955	192. 0	193. 100	194. 0
195. Electricity supply	196. 7	197. 0.558	198. 0.622	199. 0.903	200. 0	201. 85.7	202. 14.3
203. Information and communication	204. 18	205. 0.507	206. 0.586	207. 0.859	208. 0	209. 100	210. 0
211. Service total	**212. 91**	**213. 0.573**	**214. 0.632**	**215. 0.903**	**216. 4.4**	**217. 90.1**	**218. 5.5**

The DEA results for service industries are provided in Table 2b. Interestingly with respect to the deep crises of this sector two years after the 2004-2006 period that we consider, the financial and insurance activities is ranked in the top together with transport and storage. Information and communication technologies has the lowest technical efficiency among the seven service industries in our study. About 90 % of the firms need to increase their size, 6% have an optimal size and the remaining 4 % need to decrease their size.

Comparing the results for manufacturing and services, Tables 2a and 2b shows that the manufacturing sector as a whole has somewhat higher technical efficiency than service sector, while the latter has the higher scale efficiency. This fact signifies that the tendency of over-utilization of the resources in the service sector is worse than that of the manufacturing industry, while the firm size in the service sector is more optimal than the manufacturing sector. This also implies that adjusting the size of firm is a better strategy for the firms in the manufacturing sector, while decreasing unnecessary resources is a better strategy for the firms in the service sector.

Table A1 in the appendix reports comparable DEA-results to our Icelandic estimates for various countries. The average efficiencies vary considerably across studies and across countries and regions. The mean values range from 0.24 to 0.96 for manufacturing industries and from 0.50-0.96 for service industries. It is true that the average technical efficiency of the Icelandic firms is within the range of other studies, but it is lower then what has been estimated in most other countries.

4.2 DEA Slacks

As discussed in the Section 2, an existence of slacks shows that the production plan of a firm is not well-harmonized. This means that the inputs (output) can be further decreased (increased) even after the proportional reduction of inputs. By eliminating slacks a firm can show better performance. Therefore, the elimination of input/output slacks should increase the performance in the internal production process. By eliminating input and output slacks, a firm can operate on the Pareto optimal region, in which no more output can be produced without changing factor inputs. If a firm is not operating on the Pareto optimal region, it should make an effort to eliminate the internal mis-harmonization of inputs and outputs by removing unnecessary slacks so that it can obtain better performance. This makes it important to consider the slacks in our model. In this study we confine ourselves to the output slack measures.

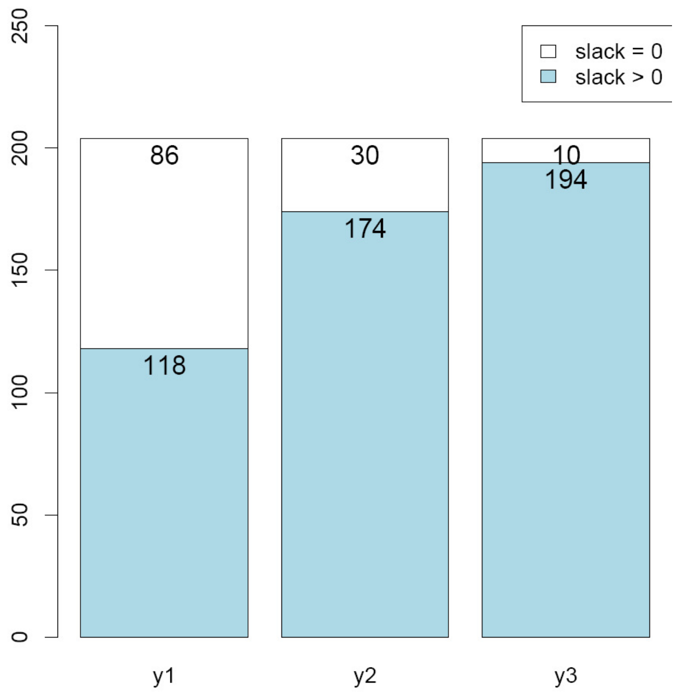


Figure 4. Distribution of three output slacks (DEA).

Note: y1– sales growth, y2 – productivity, y3 –product innovation.

Figure 4 displays the distributions of output slacks and show whether they are zero or not. Three different bins are reported. y1 is sales growth y2 productivity and y3 sales income from new products. In each bin, the bottom part represents the number of firms having a slack and the upper part represents the number of firms having no slack. As can be seen in the first bin of Figure 4, 118 firms (58% of our sample) have slacks and 86 firms (42% of our sample) have no slacks in their sales growth performance. The interpretation here is that a majority of the Icelandic firms could have increased the sales during the study period by eliminating the slacks of sales growth. Regarding the sales growth, 42 % of firms are well-harmonized. These firms have been able to sell their products adequately.

The second bin shows the slacks of labour productivity. The major finding here that there is a large potential for increasing productivity among the Icelandic firms. Only 30 firms, which is equivalent to about one out of eight firms (13%), are presently maximizing the labour productivity.

The final bin (y3) presents the distribution of the slacks of innovation output, which is measured as sales income per employee from new products lunched on the market during the period 2004-2006. Quite remarkably, 95 % (194 out of 204 firms) of the firms in both manufacturing and services have failed to use their R&D and labour input efficiently in their innovation engagement. This indicates that Icelandic firms are not benefiting much from their efforts to create new innovative products. Potential sources for this deficiency might be lack of sufficient competition, an over-heated economy with “too easy money” during the period 2004-2006.

In sum, the slack analysis indicates that the Icelandic firms do not appear to obtain adequate product innovation or to secure sufficient labor productivity, whilst they partly seem to have succeeded in increasing volume of sales.

4.3 Results of Imprecise DEA

In order to include the categorical variables into the analysis of the performance of the Icelandic firms, we exploited the imprecise DEA. The categorical variables contains information on intellectual property rights, financial support from EU or the Icelandic central government, and presence of process innovation. The continuous input and output variables in the IDEA model are the same as the DEA model. Hence, our IDEA model has five inputs (three imprecise data among five inputs) and three outputs (all output variables are continuous variables).

As discussed above, we exploited only the CRS IDEA model since the VRS IDEA has not been theoretically proposed yet. The distribution of technical efficiency of the Icelandic firms is presented in Figure 5. Except for the fact that the number of firms with technical efficiency less than 0.5 is dramatically decreased, the overall shape of distribution is similar to the conventional DEA-results. Figure 5 also shows that the majority of the Icelandic firms are technically inefficient. In our sample 95 % of firms (190 out of 204 firms) are technically inefficient. This result is similar to that of the conventional CRS-DEA.

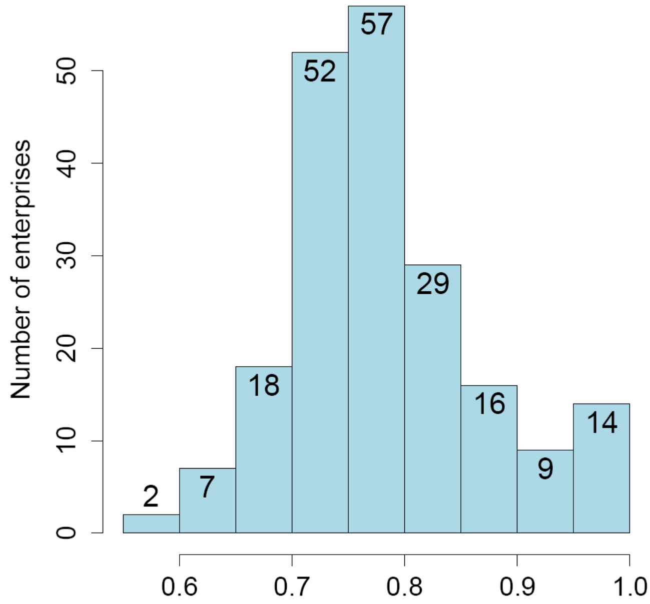


Figure 5. Efficiency distribution of technical efficiency using IDEA

Although the distribution of the score-values are similar between the two models, the mean value of the technical efficiency under IDEA is much larger than that of the conventional DEA (0.79 and 0.58, respectively.) A Mann-Whitney test[5] under the null hypothesis that two efficiency scores have the same value of mean is rejected at the 1% level of significance, which means that the average efficiency score of the IDEA is larger than that of the conventional DEA.

[5] Mann-Whitney test serves to test the hypothesis that the two groups belong to the same population with given independent data belong to two groups. The Mann-Whitney test statistics approximately follows standard normal distribution. Interested readers can refer to Cooper (2000).

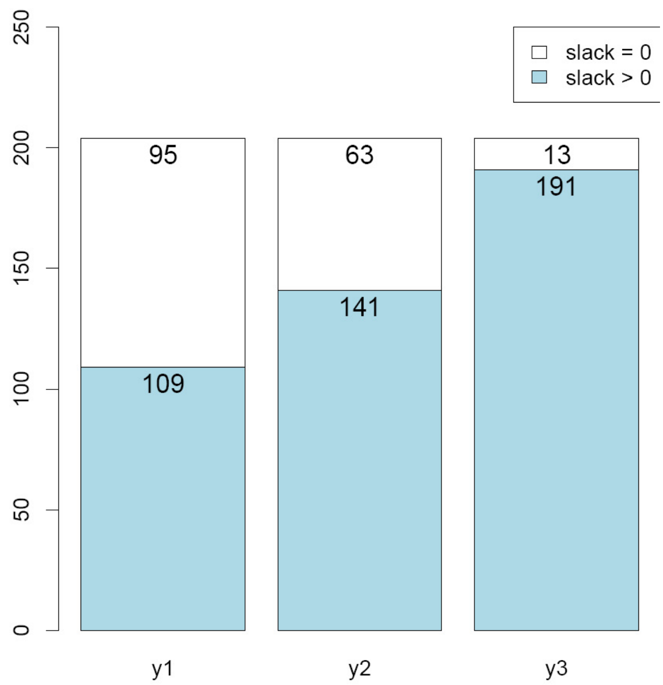


Figure 6. Distribution of three output slacks (IDEA).

Note: y1– sales growth, y2 – productivity, y3 –product innovation.

Just like the conventional DEA, an existence of slack of output in IDEA signifies that the corresponding output can be further produced by an amount of slack. Figure 6 illustrates the distributions of output slacks which show whether they are zero or not. This figure gives us a very similar story discussed in the result of the conventional DEA. The Icelandic firms could have increased their performance if they succeeded in harmonization of their production plan. This unsatisfactory mis-harmonization mainly results from the product innovation (bin y3). By launching and selling more new products on the market, alternatively launching and selling innovative products with higher market value, the Icelandic firms could have increased their performance.

4.4 Sensitivity test

We also divide our sample into two subsets in order to examine whether or not there exists a difference of technical efficiency between innovative and non-innovative firms. We estimate the technical efficiency within each subsample by means of DEA and IDEA. The results show that the innovative group have only slightly higher technical efficiency than non-innovative group. Our test statistics indicates no significant difference in technical efficiencies between innovative firms and non-innovative firms.

Following Nunamaker (1985), in addition, we conduct a second sensitivity test and examine the variability of technical efficiencies by removing some of the variables from our model. The models with removed variables are named *reduced models* in contrast to the ordinary model. If the reduced models only have minor changes in the rankings of technical efficiencies compared with our ordinary model specification, the latter can be considered as robust. In the sensitivity analysis, Spearman's rank correlation is calculated for the examination of changes of the rankings across model specifications[6]. The test results indicate that there exist only small differences in the rankings of technical efficiencies between the ordinary model and the reduced models. This means that the variables in the ordinary model are properly chosen for the empirical investigation. See Appendix, Table A2.

5. Conclusion

This paper has studied performance of Icelandic firms in the period that preceded the 2008-collapse. The objective was to test the hypothesis that the overall conditions for

[6] Spearman's rank correlation coefficient calculates the correlation coefficient between two variables, each of which is converted to ranking before calculating the correlation coefficient.

innovativeness, efficiency and productivity was weak in the booming and over-heated economy in absence of strong external pressure on a disciplinary economic policy.

Using Data Envelopment Analysis (DEA) the study investigated the relationship between investment in R&D and labour and economic output in terms of new innovations, productivity and sales growth. The analysis used 204 randomly selected firm level observations for the period 2004-2006.

A key result in the study is that a substantial fraction of the Icelandic firms can be considered as non-efficient in the sense that they are not using the best practice production technology. By switching production methods, many Icelandic firms have a potential for increasing output without increasing the amount of input factors. For other firms, the analysis suggests that the present level of production can be reached with less resources if the production process improves.

Comparing the results for manufacturing and services it was found that the manufacturing sector as a whole has somewhat higher technical efficiency than service sector, while the latter has the higher scale efficiency. The interpretation is the following: The average service firm has a more optimal size than the average manufacturing firm. The utilization of the existing production resources, however, is more efficient in manufacturing.

A policy conclusion to draw from the study is that the Icelandic economy as a whole will benefit from an increased market share for some firms and a more lean production process among other firms. The manufacturing firms are typically too small and they will use their production resources (employment and R&D investments) more efficient if the market (and firm size) expands. Among foremost services, there is potential for increasing the efficiency by reducing excessive input resources.

A major limitation for the increased efficiency of the Icelandic economy is the small size of the internal market and the distance to both neighbouring markets and foreign competitors. But during the period 2004-2006 the overheated economy and lack of a disciplinary economic policy hampered the necessary process of a continuously development of production efficiency. With a strong domestic demand and a weak competition, innovativeness and increased productivity were not on the top on the agenda among the Icelandic firms in the period that preceded the 2008 collapse. Since then, the conditions have radically changed.

References

Banker, R. D., Charnes, A., Cooper W. W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1079-1092.

Banker, R. D., Morey, R. C., 1986a. Efficiency analysis for exgenously fixed inputs and outputs. Operations Research 34, 513–521.

Bozec, R., Dia, M., 2007. Board structure and firm technical efficiency: Evidence from Canadian state-owned enterprises. European Journal of Operational Research 177, 1734-1750.

Brown, R., 2006. Mismanagement or mismeasurement? Pitfalls and protocols for DEA studies in the financial services sector. European Journal of Operational Research 174, 1100-1116.

Castellacci, F., Zheng, J., 2008. Technological regimes, Schumpeterian patterns of innovation and firm level productivity growth. MICRO-DYN working paper no. 06/08.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429-444.

Cooper, W. W., Park, K. S., Yu, G., 1999. IDEA and AR-IDEA: Models for dealing with imprecise data in DEA. Management Science 45, 597–607.

Cooper, W. W., Seiford, L. M., Tone, K., 2000. Data envelopment analysis: A comprehensive text with models, applications, references. Springer, Massachusetts.

Dimara, E., Skuras, D., Tsekouras, K., Tzelepis, D., 2008. Productive efficiency and firm exit in the food sector. Food Policy 33, 185-196.

Düzakin, E., Düzakin, H., 2007. Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of 500 major industrial enterprises in Turkey. European Journal of Operation Research 182, 1412-1432.

Göran, B., Lindblom, T., 2008. Evaluating the performance of Swedish savings banks according to service efficiency. European Journal of Operational Research 185, 1663-1673.

Guan, J. C., Yam, R. C. M., Mok, C. K., Ma, N., 2006. A study of the relationship between competitiveness and technological innovation capability based on DEA models. European Journal of Operational Research 170, 971-986.

Keh, H. T., Chu, S., 2003. Retail productivity and scale economies at the firm level: a DEA approach. OMEGA 31, 75-82.

Kim, S. H., Park, C. G., Park, G. S., 1999. An application of data envelopment analysis in telephone offices evaluation with partial data. Computer & Operations Research 26, 59–72.

Pentzaropoulos, G. C., Giokas, D. I., 2002. Comparing the operational efficiency of the main European telecommunications organizations: A quantitative analysis. Telecommunications Policy 26, 595-606.

Ross, A., Ernstberger, K., 2006. Benchmarking the IT productivity paradox: Recent evidence from the manufacturing sector. Mathematical and Computer Modelling 44. 30-42.

Sueyoshi T., 1999. Tariff structure of Japanese electric power companies: An empirical analysis using DEA. European Journal of Operational Research 118, 350-374.

Soteriou, A., Zenios, S., 1999. using data envelopment analysis for costing bank products. European Journal of Operational Research 114, 234-248.

Thanassoulis, E., 2001. Introduction to the theory and application of data envelopment analysis - A foundation text with integrated software. Springer, Massachusetts.

Tsai, H.-C., Chen, C.-M., Tzeng, G.-H., 2006. The comparative productivity efficiency for global telecoms. International Journal of Production Economics 103, 509–526.

Wang, C. H., Gopal, R. D., Zionts, S., Use of data envelopment analysis in assessing information technology impact on firm performance. Annals of Operations Research 73, 191-213.

Wu, Z. B., Yeung, G., Mok, V., Han, Z., 2007. Firm-specific knowledge and technical efficiency of watch and clock manufacturing firms in China. International Journal of Production Economics 107, 317–332.

Yang, J.-C., 2006. The efficiency of SMEs in the global market: Measuring the Korean performance. Journal of Policy Modeling 28, 861–876.

Zhu, J., 2000. Multi-factor performance measure model with an application to Fortune 500 companies. European Journal of Operational Research 123, 105-124.

Zhu, J., 2004. Imprecise DEA via standard linear DEA models with a revisit to a Korean mobile telecommunication company. Operations Research 52, 323–329.

Zhu, J., Shen, Z. H., 1995, A discussion of testing DMUs' returns to scale. European Journal of Operational Research 81, 590-596.

A. Appendix

A.1. DEA models and slacks

A.1.1. Models for DEA with continuous variables

For measuring efficiency of DMUs with an assumption of using only continuous variables in production process, the input-oriented CRS and VRS models was used in this study. We assume that there are n DMUs which produces s outputs, $\mathbf{y} \in R_S^+$, using m inputs, $\mathbf{x} \in R_m^+$. Then the technical efficiency of DMU k under CRS assumption can be evaluated by solving the followings:

$$\begin{aligned} &\min \quad \theta_k^c - \varepsilon\left(\sum_{i=1}^{s} S_i^- + \sum_{r=1}^{m} S_r^+\right) \\ &s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta_0 x_{ik}, \quad i = 1, 2, \cdots, m, \\ &\qquad \sum_{j=1}^{n} \lambda_j y_{ij} - S_r^+ = y_{rk}, \qquad r = 1, 2, \cdots, s, \\ &\qquad \theta_k^c,\ \lambda_j,\ S_i^-,\ S_r^+ \geq 0, \end{aligned} \tag{A1}$$

where θ_k^c is the objective function's value; ε is a non-Archimedean infinitesimal, which is introduced by Charnes et al. (1979) in order to overcome the difficulties of testing multi-optimum solutions; λ_j is a convex coefficient; x_{ij} is the ith input of firm j, where $i = 1, 2, \cdots, m$; y_{rj} is the rth output of firm j, where $r = 1, 2, \cdots, s$; S_r^- is a non-negative output slack and S_i^+ is a non-negative input slack; the subscription k indicates the DMU k. We hereafter refer model shown in equation (A1) as CRS-DEA model.

If the value of an optimal objective function of DMU k, θ_k^c, equals to unity and all input and output slack variables are equal to zero, then enterprise k is CRS-efficient and is operating on the CRS frontier. In such case enterprise k is regarded as being fully utilizing its inputs in producing outputs. Otherwise, if θ_k^c is not equal to (equivalently, less than) unity and/or some of slacks have non-zero values, then enterprise k is not CRS-efficient, which implies that some resources are still being over-utilized. The inefficiency may be caused by improper or inefficient harmonization of resources in the enterprise. The enterprise can eliminate the inefficiency through the benchmarking of the enterprises on the production frontiers. Therefore, the value of technical inefficiency, $(1-\theta_k^c)$, can be regarded as a measure of a possible proportionate input saving. The larger the θ_k^c, the better technical efficiency of enterprise k is. In a geometrical perspective, the technical efficiency measure of enterprise k is the ratio of 'the distance from the origin to the best-practice frontier' to 'the distance from the origin to enterprise k'. In other words, the small value of θ_k^c signifies that the gap between the best-practice frontier and the enterprise k is large.

In the CRS-model shown in equation (A1) DMUs operating on the best-practice frontier represent both technical efficiency and scale efficiency, which represents that all of them are producing their outputs on the Most Productivity Scale Size (MPSS) (Banker and Morey, 1986a). Since this assumption is too strong to impose in practice, a more flexible assumption is needed for allowing an increasing-returns-to-scale (IRS) as well as a decreasing-returns-to-scale (DRS). By incorporating an additional constraint of $\sum_{j=1}^{n}\lambda_j = 1$ into the CRS models in equation (A1), the variable returns-to-scale model (hereafter, VRS-DEA) can be expressed as follows (Banker et al., 1984):

$$
\begin{aligned}
\min \quad & \theta_k^v - \varepsilon\left(\sum_{i=1}^{s} S_i^- + \sum_{r=1}^{m} S_r^+\right) \\
s.t. \quad & \sum_{j=1}^{n}\lambda_j x_{ij} + S_i^- = \theta_k^v x_{ik}, \quad i = 1,2,\cdots,m, \\
& \sum_{j=1}^{n}\lambda_j y_{ij} - S_r^+ = y_{rk}, \qquad r = 1,2,\cdots,s, \\
& \sum_{j=1}^{n}\lambda_j = 1 \\
& \theta_k^v,\ \lambda_j,\ S_i^-,\ S_r^+ \geq 0,
\end{aligned} \tag{A2}
$$

where θ_k^v is the value of the objective function.

VRS-DEA model can be used in measuring the pure technical efficiency and the scale efficiency (Banker et al., 1984; Zhu, 2000). Scale efficiency can be defined as the ratio of the technical efficiency under the CRS assumption to the technical efficiency under the VRS assumption, i.e., θ_k^c / θ_k^v. If scale efficiency of enterprise k is unity then the enterprise is regarded to be scale efficient. Then, only enterprises having unit value of scale efficiency is operating on MPSS. If $\theta_k^c / \theta_k^v < 1$, enterprise k is scale inefficient. Therefore, we need to determine whether IRS or DRS is the primary cause of scale efficiency. Zhu and Shen (1995) provide the diagnostic tool for the criteria, in which a) If the CRS technical efficiency score is equivalent to the VRS technical efficiency score, then the CRS prevails, b) otherwise, if the CRS and VRS technical efficiency score are not equal, then $\sum_{j=1}^{n}\lambda_j < 1$ indicates IRS whilst $\sum_{j=1}^{n}\lambda_j > 1$ indicates DRS.

A.2.2 Model for DEA with imprecise variables

The conventional DEA requires that the data for all inputs and outputs are continuous. When some inputs and outputs are unknown decision variables, such as ordinal data, the DEA model becomes nonlinear programming problem and is called imprecise DEA (IDEA) (Cooper et al., 1999). Since this nonlinear programming requires the special computational codes for each evaluation, an alternative algorithm for converting this nonlinear programming to the linear form has been required. This nonlinear programming can be easily converted to the linear programming by Zhu (2004)[7]. In this study we employ the model of Zhu (2004) to evaluate the technical efficiency of Icelandic firms regarding imprecise inputs and outputs along with continuous variables. Also note that we only deal with CRS-IDEA since VRS-IDEA has not been successfully developed yet. We retain the assumptions and mathematical notations of the conventional CRS-DEA models. However, an output set is divided into two sets, each of which respectively has continuous variables and imprecise variables, and an input set is also divided into two sets. Let us denote an output set with imprecise variables as DO and an input set with imprecise variables as DI. The imprecise data (in this study, we confine the imprecise data within the ordinal data) can be expressed as

[7] A brief history and methodological development are well summarized in Zhu (2003).

$$y_{rj} \leq y_{rk} \ \text{ and } \ x_{ij} \leq x_{ik} \quad \forall j \neq k, \quad \text{for } r \in DO, \ i \in DI \,. \tag{A3}$$

Or to simplify the presentation,

$$\begin{aligned} & y_{r1} \leq y_{r2} \leq \cdots \leq y_{r,k-1} \leq y_{rk} \leq y_{r,k+1} \leq \cdots \leq y_{rn}, \quad r \in DO \\ & x_{i1} \leq x_{i2} \leq \cdots \leq x_{i,k-1} \leq x_{ik} \leq x_{i,k+1} \leq \cdots \leq x_{in}, \quad i \in DI. \end{aligned} \tag{A4}$$

Then, following Theorem 1 in Zhu (2004), imprecise DEA with ordinal data can be expressed as follows:

$$\begin{aligned} \min \quad & \theta_k^i - \varepsilon\Big(\sum_{i \notin DI} S_i^- + \sum_{i \in DI} S_i^- + \sum_{i \notin DO} S_i^+ + \sum_{i \in DO} S_i^+\Big) \\ s.t. \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- \qquad\quad = \theta_k x_{ik}, \quad i \notin DI \\ & \sum_{j \neq o} \lambda_j \overline{x}_{ij} + \lambda_k \underline{x}_{ik} + S_i^- = \theta_k \underline{x}_{ik}, \quad i \in DI \\ & \sum_{j=1}^{n} \lambda_j y_{ij} - S_r^+ \qquad\quad = y_{rk}, \qquad r \notin DO \\ & \sum_{j \neq o} \lambda_j \underline{y}_{rj} + \lambda_k \overline{y}_{rk} - S_i^+ = \overline{y}_{rk}, \quad i \in DI \\ & \theta_k^v, \ \lambda_j, \ S_i^-, \ S_r^+ \geq 0, \end{aligned} \tag{A5}$$

where the bar under symbol indicates the lower bound of the corresponding ordinal variable and the bar above symbol indicates the upper bound of the corresponding ordinal variable.

In order to solve the linear programming shown in equation (A5), the following tricks are useful for converting the nonlinear programming into the linear programming. By setting $y_{rk} = x_{rk} = 1$ for DMU k, $\underline{y}_{rj} = 0$ and $\underline{x}_{ij} = 1$ for DMU j ($j = 1, \cdots, k-1$) and $\overline{y}_{rj} = 1$ and $\overline{x}_{ij} = n$ for DMU j ($j = k+1, \cdots, n$). By this procedure, the nonlinear imprecise DEA problem can be converted to the linear programming with a set of exact data.

A.1.3 Slacks in DEA

Even though inefficient DMUs can be projected to the frontier so that they can benchmark the efficient firms to obtain the better technical efficiency, their resources can be further reduced and their outputs can be further produced by eliminating input input/output slacks. In other words, DMUs can move onto the point of the Pareto optimal production plan by getting rid of input slacks and by securing output slacks even after proportionately eliminating input excesses. The projection of an inefficient firm k onto the frontier can be expressed as $\theta_k \mathbf{x}_k - \mathbf{S}^{*-}$, where $\mathbf{x}_k$, θ_k and $\mathbf{S}^{*-}$ are the input vector, the technical efficiency and the input slack vector of firm k, respectively. In this manner the calculation procedure in the input-oriented DEA can be interpreted as a function by which input vector $\mathbf{x}_k$ is proportionately reduced by θ_k^v followed by the further reduction of input slacks $\mathbf{S}^{*-}$ such that a firm produces at least the present level of output. Likewise the interpretation of input slacks, $\mathbf{y}_k + \mathbf{S}^{*+}$ can be interpreted as a function in which output vector $\mathbf{y}_k$ can be further produced by a amount of output slack vector $\mathbf{S}^{*+}$.

A.2. Technical efficiency in previous studies

By means of DEA-related approaches, technical efficiencies of various industries have been measured. Table A1 summarizes the average technical efficiency according to the industries and methodologies. Since the technical efficiency measure is sensitive to the sample and input/output selection, the average efficiencies vary across studies. The mean values of the manufacturing industries range from 0.24 to 0.96. The mean values of the service industries range from 0.50 to 0.96. Although the technical efficiencies vary across sectors, the average technical efficiencies of the Icelandic firms appear to vary within those ranges.

Table A1. Average technical efficiencies at firm-level in previous studies.

Manufacturing

Study	Sample	Average efficiency	Methodology
Dimara et al. (2008)	5503 Greek food firms, 1989-1996	0.24	Input oriented CRS-DEA and VRS-DEA
Düzakin and Düzakin (2007)	480 Turkish manufacturing firms, 2003	0.12-1.24*	Output oriented slack based model.
Wu et al. (2007)	145 Chinese watch and clock manufacturer, 2002	0.52	Input oriented CRS-DEA
Bozec and Dia (2007)	14 Canadian State owned enterprises, 1976-2001	0.85-0.94	Input oriented CRS-DEA and VRS-DEA
Guan et al. (2006)	182 Chinese manufacturing enterprises	0.78-0.86	Input oriented CRS-DEA and VRS-DEA
Ross and Ernstberger (2006)	51 U.S. manufacturing firms, 1999	0.86-0.96	Input oriented CRS-DEA and VRS-DEA
Yang (2006)	267 Korean SMEs, 1999-2002	0.45-0.87 (1.94-3.22)**	Input and output oriented CRS-DEA and VRS-DEA
Wang et al. (1997)	22 global manufacturing companies, 1987-1989	0.06-1.00***	Input oriented VRS-DEA

Notes:

* Authors report only the average efficiency by industry. Overall efficiency is not reported

** Numbers in parenthesis represents output oriented efficiency.

***Since sample size is small, raw efficiencies are presented.

Services

Study	Sample	Average efficiency	Methodology
Göran and Lindblom (2008)	88 Swedish banks, 1997-2001	0.66-0.69	Input oriented CRS-DEA
Brown, R. (2006)	271 Australian credit unions, 1993-1995	0.63-0.92	Output oriented VRS-DEA
Tsai et al. (2006)	39 global telecommunication companies, 2003	0.75-0.89	Input oriented CRS-DEA and VRS-DEA
Keh and Chu (2003)	13 U.S. retailers, 1988-1997	0.94-1.00***	Input oriented VRS-DEA
Pentzaropoulos and Giokas (2002)	19 European telecommunication operators,	0.53-1.00***	Output oriented VRS-DEA
Sueyoshi (1999)	9 Japanese electric power companies, 1993-1994.	0.78-1.00***	Cost based DEA
Soteriou and Zenios (1999)	22 Cyprus commercial banks, 1994	0.96	Output oriented CRS-DEA and VRS-DEA

Notes:

* Authors report only the average efficiency by industry. Overall efficiency is not reported

** Numbers in parenthesis represents output oriented efficiency.

***Since sample size is small, raw efficiencies are presented.

Table A2. Model specification and spearman's rank correlation.

Output	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales growth	○	○	○		○		
Productivity	○	○		○		○	
Innovation Income	○		○	○			○
Spearman's ρ	-	0.999	0.894	0.999	0.299	0.999	0.893

Notes

(1) ○ denotes variables include per specification.

(2) Numbers in the last row represent the spearman's rank correlation coefficient between technical efficiencies of the model specified in each column and technical efficiencies of model (1).