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The Icelandic Economy: A victim of the financial crisis or simply inefficient? [1]

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Abstract

Iceland, one of the smallest European economies, was hit severely by the 2008-financial crisis. This paper uses a firm-level Community Innovation Survey (CIS) data set to consider the economy in the period preceding the collapse of its financial system. We examine the linkage between the crisis and innovativeness from the perspective of technical efficiency by means of the Data Envelopment Analysis of 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 considered technically efficient, while services firms typically use excessive resources in their production process. A remarkably weak performance in transforming R&D and labor efforts into successful innovations is observed. Based on the empirical results, suitable policy implications are suggested to remedy the inoptimal production structure and help economic recovery.

Keywords: Technical efficiency, R&D, Innovation, Productivity, Manufacturing, Services, Iceland

JEL Classification: C67; D24; D57; L25; L60; L80

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1. Introduction

Iceland is one of the smallest European economies with a labor force of only about 170,000. The country has long been considered a politically stable Scandinavian-type economy with a high standard of living, low unemployment, equal distribution of income and opportunities, advanced health care and a well-functioning education system.[2] The major trade partners of Iceland are other Northern-European countries and the USA. The economy depends heavily on its fishery-related industries which in recent years have been diversified into growing manufacturing and service industries.

Several branches such as financial services, software, biotechnology and tourism showed a strong development and growth especially during the 1990s, continuing into the 2000s. However restructuring of the economy and strengthening through opening up its financial market to countries with advanced financial market systems led to the collapse of the economy. It is commonly believed that the collapse was due to the swift transition without adequate evaluation of the preparations and consequences of the 'economic boom' immediately preceding the financial collapse.

After the collapse of Iceland's financial system in early autumn 2008, the Icelandic currency (Krona) depreciated by about 50% against the Euro. The economy shrank drastically, real wages fell by about 15% and unemployment started to grow rapidly. This shocking and unfavorable economic situation, which overwhelmed the whole country in less than a month, severely affected the confidence of consumers, producers, investors and the decision makers.

This paper considers the Icelandic economy a couple of years before the recent financial collapse in order to diagnose the competitiveness of manufacturing and service industries from the perspective of technical efficiency in production. The analysis uses 204 randomly-selected firm-level observations for the period 2004-2006. The first two years of this period were characterized by a strong economic boom with an annual GDP growth rate of above 6 %, followed by a mini-crisis in 2006 with a growth rate just over 1 %. The current crisis is used as a reference point without being part of the study period.

The main objective of our study is to explore how efficiently the Icelandic Economy used its factor inputs such as labour, capital stock and R&D resources during the period before the current (2009) crisis. The technical efficiency was extreme in several respects. First, the economy was over-heated with a negligible unemployment rate and a large and growing number of non-residents working for Icelandic companies. Second, the total assets of the banking sector increased to 800% of GDP in 2006 (from being under 100% in 2000). Third, the countries net external debt increased from just over 100% of GDP in 2004 to over 200% in 2006; and, finally, the inflation rate increased from 2.0% to 7.0% between 2003 and 2006 (during the period, the target rate for the Iceland Central bank was only 1.5%).

[2] Per capita GDP of Iceland was $40,000 (PPP) in 2007. Iceland was ranked number six among the OECD member countries (World Bank).

Given the background to the economic crisis and the way it developed, we try here to formulate and test hypotheses to partially explain the crisis and its impacts. The main hypothesis is that the overall conditions for innovativeness and efficiency were not sufficient in the booming and over-heated period.

Unlike most methodological approaches, we employ data envelopment analysis (DEA) for the empirical investigation. A common empirical approach for analyzing relationships among R&D, innovation, productivity and growth is the parametric model of a Cobb-Douglas form. A growing number of these studies use the same kind of firm-level data as we do in this paper, namely from the Community Innovation Survey (CIS).[3] The internationally harmonized CIS data contains a rich variety of information on innovative organizations and activities, firm characteristics and economic performance.

Only a small strand of the literature uses non-parametric approaches to analyze the performance of firms with the help of CIS data. To our knowledge, only Castellacci and Cheng (2008) employ the DEA-type approach for the aforementioned purposes. However, for methodological reasons these studies do not include categorical variables in the empirical investigation. Our study methodologically fills the gap in that it employs the most recently developed methodology for including categorical variables in the analysis.

DEA employs linear programming to calculate the performance, *i.e.*, technical efficiency, of decision-making units (DMUs) by constructing the best-practice frontier. From methodological and sensitivity perspectives, the data envelopment analysis is regarded as a counterpart of the parametric estimation approach, such as the stochastic frontier analysis, in that it does not require any assumptions on the underlying functional form of production activities. Moreover, it is free from the distributional assumption of the error term and can easily deal with multi-input and multi-output bundles of production processes.

In DEA the efficiency of each DMU can be estimated through n optimization problems (where n is the number of DMUs) by constructing the best-practice frontier with observed input-output bundles of the DMUs. Contrary to the single optimization problem of the traditional parametric statistical approaches, DEA is a DMU-specific optimization approach. We believe that DEA can appropriately be used to test the aforementioned hypotheses. In doing so, we employ both the conventional DEA models and the imprecise DEA model (IDEA). With the latter model binary variables can be included in analyzing technical efficiency scores. This paper uses a model found in Zhu (2004).

DEA has been widely exploited in studies of different industrial sectors in the field of industrial economics and management, in which performance evaluation and benchmarking studies are mainly considered. For instance, Zhu (2000) employs DEA

[3] For a selection of innovation studies based on CIS data sets from different countries see: Hall and Mairesse (1995), Crepon, Duduet and Mairesse (1998), Lööf and Heshmati (2006) and Oh et al (2008).

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 for the period between 2000 and 2002. One of the few DEA-studies that are close to the general framework of our 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 based on a non-parametric framework. Using DEA the following main findings emerge from our study. First, about 90% of the Icelandic firms can be classified as non-efficient in the process of transforming labor, capital stock and R&D efforts into output in terms of innovations, productivity and growth. Second, the manufacturing sector as a whole has somewhat lower technical efficiency than the services sector, while in the latter around 50% of firms are operating in the decreasing returns-to-scale region. This implies that, in Iceland, reducing unnecessary resources is a more optimal strategy for the manufacturing sector, while adjusting the size of firm is a better strategy for increasing efficiency in the service sector. Third, Icelandic firms have not fully exploited the R&D activities to extract innovativeness, which is the key factor for fostering the economy in a sustainable manner.

The remaining part of this paper is organized as follows: Section 2 briefly introduces the DEA methodology. Section 3 explores the data. Section 4 contains the results, followed by brief concluding remarks in Section 5.

2. Empirical Models

This section presents a brief introduction to DEA. A more detailed model with mathematical notations is provided in Appendix A.2. DEA is a method for measuring comparative or relative efficiency as a proxy for the performance of DMUs (in this paper the 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 to measure i) how much inputs can be reduced at most for a given value of outputs when the production process is technically efficient, or ii) how much outputs are increased for a given set of inputs when the production process is technically efficient. The former measure is referred to as the input-oriented technical efficiency measure and the latter is referred to as the output-oriented technical efficiency measure.

In order to measure the potential contraction of inputs or the potential expansion of

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

outputs, particular forms of returns-to-scale need to be assumed in constructing a *production possibility set* (PPS). The conventional assumptions are a constant returns-to-scale (CRS) or a variable returns-to-scale (VRS). In the latter assumption, increasing, constant and decreasing returns-to-scale are allowed. In the CRS assumption, outputs will increase proportionally to inputs on the frontier. In the VRS assumptions, on the other hand, the returns to inputs will vary. In practice VRS is often preferred, but the choice is not based on any statistical testing procedure.

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. The PPS under the CRS assumption is below the thick solid line from the origin, and the PPS under the VRS assumption is below the piecewise linear thick solid line. 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 DA/DF and the output-oriented technical efficiency under VRS is measured as DA/DE Thus, the output-oriented technical efficiency measures potential expansion of an output with a given input.

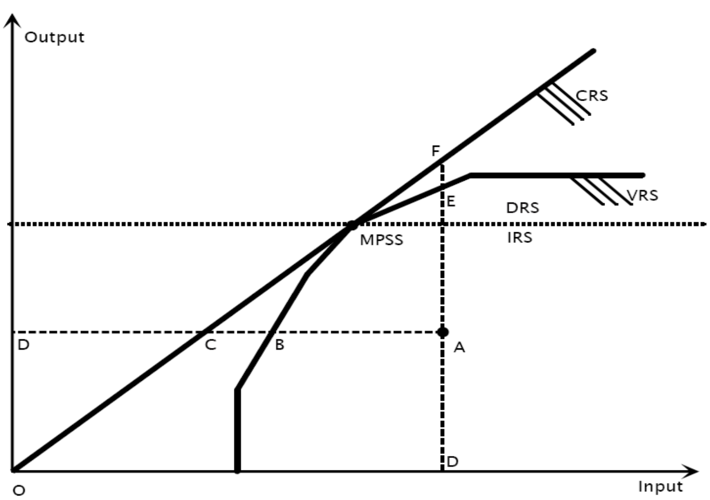

Figure 1. CRS and VRS production possibility sets and technical efficiency.

The ratio of CRS efficiency to VRS efficiency is defined as scale efficiency. The larger the ratio, the closer a DMU is operating to the *Most Productive Scale Size* (MPSS**)**. At MPSS, the DMUs will exhibit the maximum average productivity. The 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 the *output-oriented measure* is DE/DF. Hence, the scale efficiency shows how far a DMU is located from the MPSS. If a DMU is operating below the MPSS, then it is operating in the increasing returns-to-scale (IRS) region. If a DMU is operating above the MPSS, then it is operating in the decreasing returns-to-scale (DRS) region. In the increasing returns-to-scale region, increasing the size of DMU will increase average productivity. In the decreasing returns-to-scale region, on the other hand, decreasing the size of DMU will increase average productivity.

Figure 2 provides an illustration of a two-input case. 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* produces one unit of output with an input bundle given as the point A. The DMUs *C, D* and *E* constitute the technology frontier, and the technical inefficiency is measured relatively to this frontier.

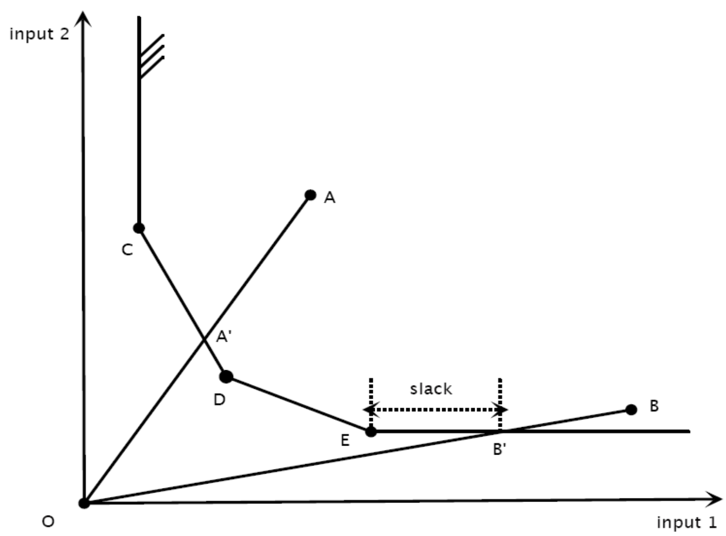

Figure 2: Production possibility set in a two inputs case.

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 may also be seen as the ratio of 'the distance from the origin to the point on the frontier towards the given point' to 'the distance from 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 refer to Cooper et al. 2000). If the technical efficiency of a DMU is equal to unity, then the DMU is technically efficient. If the technical efficiency of a DMU is less than unity, then 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, until it reaches the frontier. Consider DMU *B* in Figure 2. A proportional decrease of its input bundle moves B to B'. However, the firm can still be on the frontier after reducing Input 1 further by the amount of EB'. Now, it uses the same amount of Input 2 as previously, 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 which 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. An analogous discussion can be applied to the output space, which gives output slacks.

The Community Innovation Survey includes categorical variables on various firm characteristics. A drawback of 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 the *imprecise DEA* (IDEA). When only the continuous variables are considered, we employ the conventional DEA; when both the dummy variables and continuous variables are considered, we employ the IDEA, which was first introduced by Kim et al. (1999). We also apply the model proposed by Zhu (2004) in which the calculation process is extensively simplified compared with the original approach. Since 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 between 2004 and 2006. Economic variables such as sales and number of employees are reported for the years 2004 and 2006, while variables on innovation activities are reported only for the year 2006. Missing values in the sample have been replaced by imputed values.[5] Since capital stock data is not included in the raw CIS data set, we have estimated firm-level capital stock based on the aggregated capital stock at industrial-level, and calculated by multiplying the number of employees of firms by the capital stock per employee in the industrial sector. Data on the capital stock and number of employees at the industrial-level have been obtained from the Statistics Iceland website.

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[5] The imputation is based on the firm's own mean or, in the absence of such, the sample mean.

Table 1. Summary statistics of key variables used in the study. The economic variables are expressed in Icelandic Krona (thousands).

Variables, measurement	Mean	Std dev	Median
Output			
Sales growth, percent annually	22.40	141.00	6.70
Productivity, log	9.44	0.91	9.31
Innovation sales, log	7.69	1.43	7.71
Input			
Employment, number	60.00	116.00	26.00
Employment, log	3.46	0.96	3.37
Capital stock, log	12.25	1.66	12.38
Total R&D, log	8.76	2.93	9.60
Process innovation, dummy	0.26	0.44	0.00
Product innovation, dummy	0.47	0.50	0.00
R&D support, dummy	0.39	0.49	0.00
Intellectual property rights (IPR), dummy	0.18	0.38	0.00

Three output measures are used in this study. The first is annual sales percentage growth during 2004-2006. The summary statistics of the data presented in Table 1 show that the distribution is highly skewed to the right, indicating that a few firms have a considerably larger growth rate compared to the majority of firms. This is reflected in the large gap between the mean value (22%) and median (7%). The second output measure is labor productivity, which is calculated by dividing sales by the number of employees. As could be expected, the mean value is somewhat larger than the median, reflecting that some firms in the sample are highly productive. The final output measure is innovation sales, defined as sales income in the year 2006 from new products (product innovations) launched on the market during the period 2004-2006. Innovation sales are expressed in per employee terms. All the variables measured in monetary form are expressed as fixed 2006 prices using the producer price index.

Looking then at the input variables at 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 conducts 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%.

R&D expenditure for the typical firm in the sample corresponds 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 the 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 firms received R&D support from the government or the EU, and that 18% of the firms used the legal protection system for intellectual property rights (IPR) to protect their designs, copyrights or patents from imitation.

4. Empirical results

This section reports the results of 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 starting point for measuring technical efficiency, which determines the shape of a production possibility set when constructed from observations. The main focus is on the technical efficiencies under constant returns-to-scale (CRS) and variable returns-to-scale (VRS), both of which express how efficiently firms are using their resources. The VRS assumption allows increasing, decreasing and constant returns-to-scale. We also report the results of scale efficiency and those from an analysis of slacks.

In the CRS assumption, if production plans are on the frontier, outputs will increase proportionally to the increase of 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 of firms. The point which represents maximum average productivity is referred to as Most Productive 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 decrease of inputs. A production plan without slacks is referred to as being well-harmonized.

In this study outputs are sales growth, labor productivity and income per employee from new products and processes. The input variables are labor, capital stock and R&D expenditure per employee. When employing the IDEA, we add another three categorical variables to the above input factors. They are dummies for process innovation, public R&D support and intellectual property rights activities.

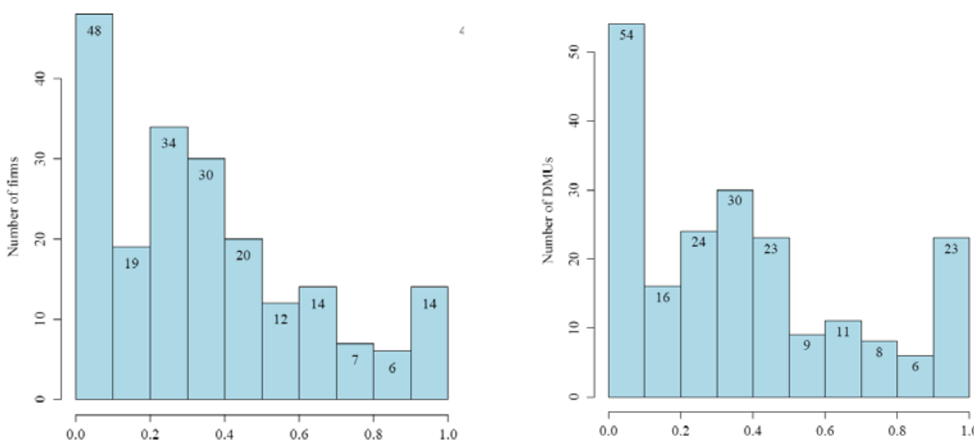
4.1 Technical efficiency: DEA

We start by presenting the results from the conventional DEA. Figure 3 shows the distributions of the CRS and VRS technical efficiency scores. Note again that the theoretical range of efficiency scores is between 0 and 1. The left panel of Figure 3 displays the distribution of the CRS scores. It can be seen that only 7% (14 out of 204) of the firms achieve CRS efficiency with a score equal to or close to 1. About 60% of the firms have CRS scores within the range of 0.20- 0.95, and 33% of them have CRS efficiency scores below 0.2.

The above figures show that the majority of the Icelandic firms can be considered non-efficient and that they make excessive use of R&D expenditures, labor and capital when producing their products and services. An alternative way of interpreting this result is that these firms could become efficient by allocating less input to production activities and thus be able to produce the present level of products with fewer resources.

The right panel of Figure 3 illustrates the distribution of the VRS efficiency score. The panel reports that about 11% of the firms (23 out of 204) are technically efficient. For the rest of the Icelandic firms, the VRS efficiency scores of most firms are distributed under 0.5.

The results of the CRS and the VRS efficiencies yield fairly robust evidence that the Icelandic firms in our investigation have not optimized their production process from the perspective of technical efficiency. In sum, about nine out of ten Icelandic firms can be classified as being non-efficient in transforming R&D efforts, labor and capital into outputs in terms of innovations, productivity and growth.



(3a) CRS efficiency distribution (3b) VRS efficiency distribution

Figure 3. Distribution of technical efficiency.

Tables 2a and 2b show the description of CRS and VRS efficiency scores aggregated for the 15 manufacturing and service industrial branches. All the industries have an average CRS efficiency between 0.58 and 0.85 and an average VRS efficiency between 0.64 and 0.89. The results of the manufacturing industries are presented in Table 2a. Considerable heterogeneity in efficiency scores can be found among different branches for the two returns-to-scale assumptions. Of the ten industrial branches, the furniture and recycling branch shows the highest average technical efficiency in terms of CRS efficiency, followed by the machinery and equipment branch. The metallic products branch is found to be the least efficient. The pattern is somewhat different if the VRS assumption is employed; the fish products branch now ranks first. This result is in line with our understanding of the Icelandic economy, which mainly depends on the fishery-related industry, and reflects the fact that the industrial structure has not changed much although an opening in the economy has been available from the 1990s.

Table 2a. DEA results for manufacturing industries.

	(1) Number of firms	(2) CRS	(3) VRS	(4) Scale effic.	(5) DRS (%)	(6) IRS (%)	(7) MPSS (%)
Fish products	19	0.339	0.436	0.835	0.0	94.7	5.3
Food products and beverages	27	0.297	0.337	0.881	0.0	100.0	0.0
Textiles and wearing apparel	9	0.227	0.280	0.791	0.0	100.0	0.0
Publishing and printing	14	0.400	0.366	0.863	0.0	92.9	7.1
Chemical and chemical products	8	0.312	0.350	0.898	0.0	100.0	0.0
Metallic products	11	0.178	0.142	0.923	9.1	90.9	0.0
Machinery and equipment	15	0.418	0.423	0.883	0.0	100.0	0.0
Electrical equipment	10	0.344	0.321	0.908	0.0	100.0	0.0
Transport equipment	7	0.329	0.351	0.908	0.0	85.7	14.3
Furniture and recycling	6	0.434	0.367	0.913	0.0	100.0	0.0
Manufacturing average	126	0.327	0.346	0.876	0.8	96.8	2.4

We now consider the four last columns of the table. Column 4 shows the results for scale efficiency; columns 5 and 6 report shares of decreasing or increasing returns to scale, and the last column shows the share of products at MPSS.

There is a need to discuss the meaning of scale efficiency, returns to scale and MPSS. Scale efficiency measures the gap between the CRS and VRS technical efficiencies. By definition, a large value of scale efficiency corresponds to a small gap between the two efficiency measures. Scale efficiency also measures how far a firm is located from the MPSS. As the name indicates, a production plan at MPSS yields the maximal productivity. If a firm is operating in the DRS (IRS) region, it needs to decrease (increase) its size to reach MPSS. By adjusting their sizes, firms can increase their average productivity.

In all the industrial branches the average scale efficiency is less than unity, implicitly indicating that the firms are not operating at MPSS. The figures in the fifth and sixth columns show the shares of manufacturing firms in the DRS and IRS regions, respectively. The figures in these columns indicate that most manufacturing firms operate in the IRS region, suggesting that the sizes of manufacturing firms are not large enough to produce in an optimal manner. The productivity of these undersized manufacturing firms can be increased if their sizes are not below optimal. As can be seen in column 7, only 2% of Icelandic firms operate at MPSS, indicating that the sizes of most firms are not optimal. This result coincides with the aforementioned results of scale efficiency.

To sum up, the following policy implication can be developed. Most of the manufacturing firms in Iceland need to adjust their firm sizes to operate in the region of optimal size. It seems that the overheated economic condition during the study period did not spill over to the manufacturing industry in terms of returns to scale and optimal-firm size.

Table 2b. DEA results for service industries.

	(1) Number of firms	(2) CRS	(3) VRS	(4) Scale effic.	(5) DRS (%)	(6) IRS (%)	(7) MPSS (%)
Electricity, gas and water supply	3	0.076	0.080	0.920	33.3	66.7	0.0
Wholesale trade and retail trade	16	0.409	0.462	0.777	43.8	31.2	25.0
Transport	23	0.202	0.229	0.867	4.3	95.7	0.0
Financial intermediation	11	0.430	0.456	0.924	36.4	54.5	9.1
Research and development	25	0.584	0.566	0.903	76.0	12.0	12.0
Service total	78	0.394	0.411	0.870	41.0	48.7	10.3

The DEA results for service industries are provided in Table 2b. The average technical efficiency of the services industry is slightly higher than that of the manufacturing industry. This result is consistent with the fact that the Icelandic economy attempted to catch up with the other developed countries by transforming the economic structure from a fishery-related manufacturing-led economy into a service-led economy in the 1990s. Industry-specific investigation reveals that the research and development branch ranks first regardless of the returns-to-scale assumptions. The average technical efficiency of the electricity, gas and water supply branch is quite low. This might be attributed to the fact that the capital stock of the branch is too large and its innovation-related outputs have been seldom produced.

The slightly higher average technical efficiency of the services industry than that of the manufacturing industry does not necessarily mean that the transition has been successful. The share of firms at MPSS reveals that only 10% of the service firms are of optimal size. This also means that 90% of firms are of sub-optimal size. Around half of these sub-optimal firms are in the DRS region, indicating that the size of these firms is unnecessarily large. The share of firms in the DRS region of the services industry (41.0%) was much larger than that of the manufacturing industry (0.8%), suggesting that the boom mainly occurred in the services industry, making service firms overheated and oversized. In the financial intermediation branch, which is commonly considered the epicenter of the financial crisis in 2008, this trend could not help but occur. Only one of ten finance-related firms operates at optimal size, whereas four out of ten firms are oversized. Services firms seem to have expanded their firm size in the boom period, in the belief that the larger size was the better for their survival and profitability.

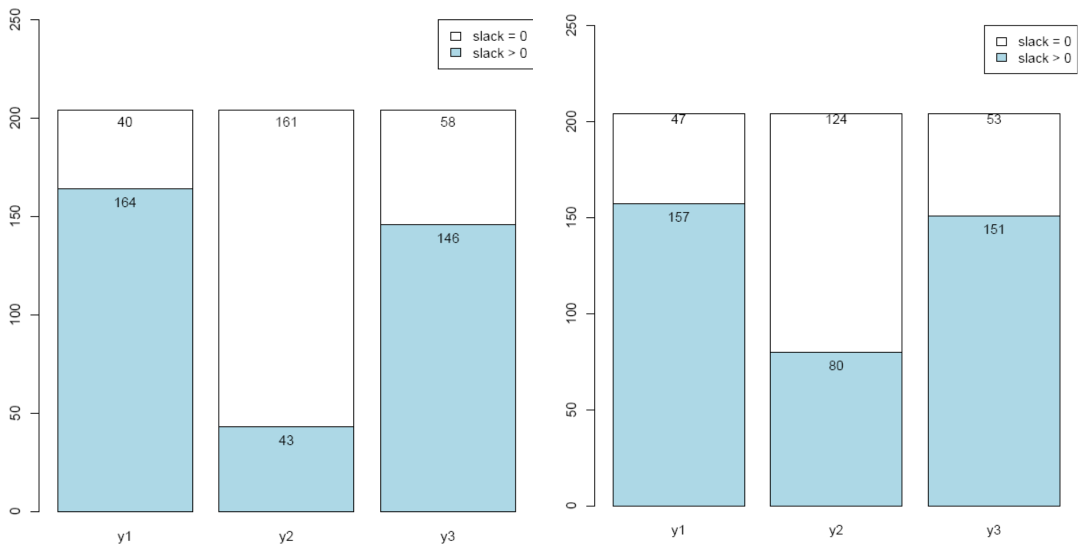
Comparing the results of manufacturing and services industries in Tables 2a and 2b, it can be seen that i) as already discussed, the manufacturing sector as a whole has somewhat lower technical efficiency than the service sector, and ii) the service industry has a higher proportion of firms in the DRS region than the manufacturing industry. This fact signifies that the tendency of over-utilization of the resources in the manufacturing sector is worse than that of the manufacturing industry *ceteris paribus*. It also indicates that a tendency of oversize in the services industry, implying that decreasing unnecessary resources is a better strategy for the firms in the manufacturing sector, whereas adjusting the size of firm is a better strategy for the firms in the services sector.

In the Appendix, Table A1 summarizes the average technical efficiency score in previous studies for comparison with this study. The average efficiencies vary considerably across studies, 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. Although it is true that the average technical efficiency of the Icelandic firms is within the range of other studies, it is lower than what has been estimated for most other countries.

4.2 DEA Slacks

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

Figure 4 displays the distributions of output slacks and whether they are zero or not. Distributions of output slacks are shown in the three bins, representing the following: sales growth (y1), productivity (y2), and sales income from new products (y3). The colored bottom part represents the number of firms with a slack and the uncolored upper part represents the number of firms without a slack. As can be seen in the first bin, 164 firms (80% of our sample) have slacks and 40 firms (20% of our sample) have no slacks in their sales growth performance. The results under the VRS assumption are almost the same. The interpretation here is that a majority of the Icelandic firms can increase their sales by eliminating their sales-growth slacks. Regarding sales growth, only around 20% of firms are well-harmonized, indicating that these firms are able to sell their products adequately.



(a) CRS (b) VRS

Figure 4. Distribution of three output slacks (DEA)

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

Both second bins show the distributions of labor-productivity slacks. They indicate that at least 60% of the firms have no slacks in labor productivity (80% under the CRS assumption; 60% under the VRS assumption), and that one out of three Icelandic firms has potential for increasing labor productivity by eliminating slacks in labor productivity. Under the CRS assumption 22 manufacturing and 21 services firms are found to have slacks. Under the VRS assumption 54 manufacturing and 26 services firms have slacks in labor productivity. Although the figures are somewhat different for the returns-to-scale assumptions, it can be deduced that it is more effective to develop industrial policies for eliminating labor-productivity slacks in the manufacturing industry than in the services industry. These policies could be, for example, i) substitution of less-productive employees with machinery, and ii) development of education systems for improving human capital.

The final bins present the distribution of the innovation-output slacks, measured as sales income per employee from new products launched during the period 2004-2006. Quite remarkably, around 75% (151 out of 204 firms) of the firms in both manufacturing and services have failed to use their R&D and labor input efficiently in their innovation engagement. This indicates that Icelandic firms are not benefiting much from their efforts to create new innovative products. Potential reasons for this deficiency might be lack of sufficient competition and an over-heated economy with "too easy money" during the period 2004-2006.

In sum, the slack analysis indicates that Icelandic firms do not appear to achieve adequate product innovation or to secure volume of sales, whilst they seem to succeed in increasing labor productivity somewhat.

4.3 Results of Imprecise DEA

In order to include the categorical variables in the analysis of the performance of Icelandic firms, we use imprecise DEA. The categorical variables used in this study contain information on intellectual property rights, financial support from the 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 six inputs (three imprecise data among six inputs) and three outputs (all output variables are continuous variables).

As discussed above, we use only the CRS IDEA model for the empirical analysis since the VRS IDEA has not been theoretically proposed yet. The distribution of technical efficiency of Icelandic firms based on CRS IDEA is presented in Figure 5. The overall shape is quite different from that of the CRS DEA result. First, the number of efficient firms increases by three, resulting in 17 firms. There might be two possible reasons for this increase of efficient firms: i) as the number of variables increases, the discriminating power is likely to be lowered, and ii) the distribution by means of the IDEA might be the unbiased one, since input-output variables used in the IDEA analysis describe the innovation-related production activities better than those in the DEA analysis. To our knowledge no method has yet been developed to ascertain the more appropriate one of the two. Hence, we only conjecture that it is highly probable that the results of IDEA explain the innovation-related production activities. Because the following findings possess the same two reasons, we will omit the reasons for the occurrences. Second, firms with a technical efficiency score of less than 0.5 are eliminated. Third, the average level of the technical efficiency score increases to some extent. Fourth, compared to the distribution of the CRS result, the distribution of the IDEA result is symmetrically centered to around 0.8. This result of symmetric shape is in line with Guan et al. (2006). However, the symmetrically shaped distribution is not common in a DEA-related study since the prior distribution of technical efficiency scores is not assumed. Finally, it is found that the majority of the Icelandic firms are technically inefficient. In our sample 92% of firms (187 out of 204 firms) are technically inefficient. This result is similar to that of the conventional CRS-DEA.

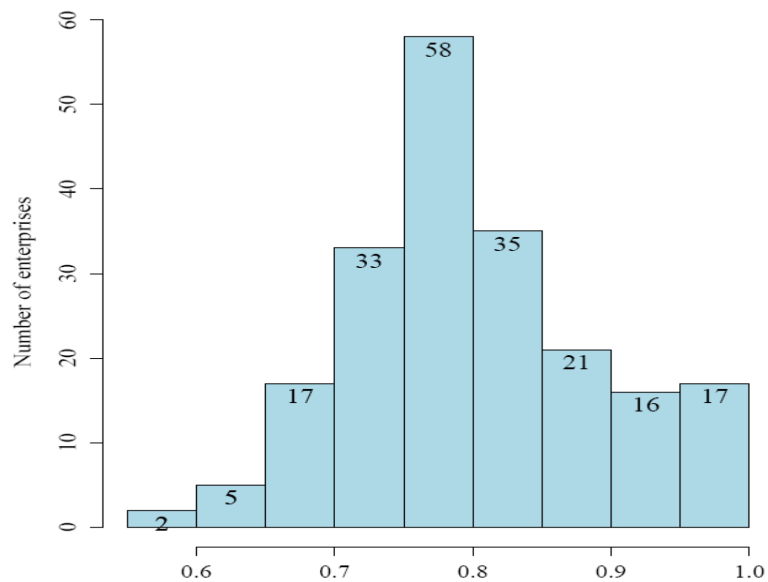


Figure 5. Efficiency distribution of technical efficiency using IDEA.

As mentioned above the average technical efficiency of the IDEA result (0.804) is somewhat higher than that of the CRS-DEA result (0.352). A Mann-Whitney test 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.[6]

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

[6] The Mann-Whitney test is used to test the hypothesis that the two groups belong to the same population with given independent data. The Mann-Whitney test statistics approximately follow standard normal distribution. Interested readers can refer to Cooper et al. (2000).

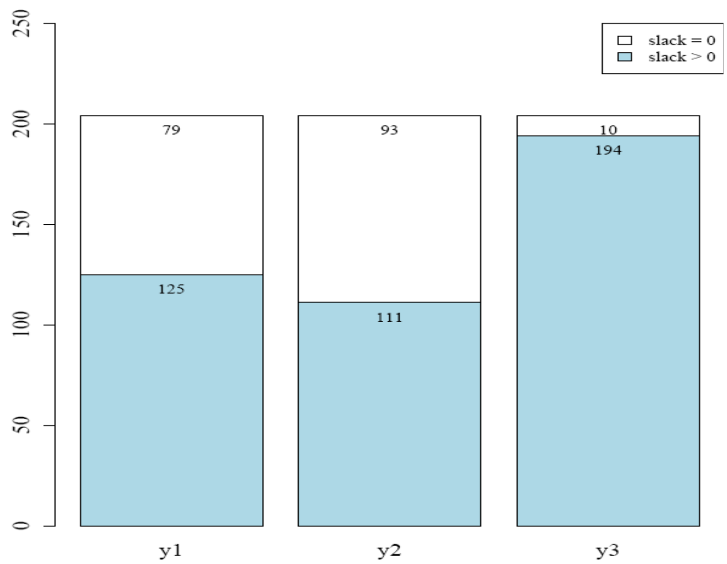


Figure 6. Distribution of three output slacks (IDEA).

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

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, and the results show that the innovative group has only slightly lower technical efficiency than the non-innovative group. However, our test statistics indicate no significant difference in technical efficiencies between innovative firms and non-innovative firms.

Following Nunamaker (1985), 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* to distinguish them from the ordinary model. If we observe only minor changes in the rankings of technical efficiency scores for the reduced models compared with our ordinary model specification, the latter can be considered as robust. In the sensitivity analysis, Spearman's rank correlation is used for the examination of changes of the rankings across model specifications.[7] The test results indicate that only small differences in the rankings of technical efficiencies exist 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 A3.

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

5. Conclusion

This paper studies the performance of Icelandic firms from the perspective of firms' technical efficiency in the period that preceded the 2008-collapse. The objective is to test the hypothesis that the overall conditions for innovativeness, efficiency and productivity of firms were weak in the booming and over-heated economy.

Using Data Envelopment Analysis (DEA) our study investigates the relationship between investment in R&D, labor and capital stock on the one hand, and economic output in terms of new innovations, labor productivity and sales growth on the other. The analysis uses 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 non-efficient in the sense that they are not using the best-practice production technology. By switching production methods, many Icelandic firms could have potential for increasing output without increasing the amount of input factors in production. For other firms, the analysis suggests that the present level of production can be reached with fewer resources if the production process is improved.

Comparing the results for manufacturing and services, it is found that the service sector as a whole has somewhat higher technical efficiency than the manufacturing sector, while most firms in the former produce in the DRS region. The interpretation is the following: manufacturing firms need to reduce their usage of input resources in producing output to achieve better technical efficiency, and service firms need to decrease their size in order to increase their average productivity.

A policy conclusion to draw from our 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 for other firms. The manufacturing firms are typically too small and they should use their production resources (employment and R&D investments) more efficiently. For services in particular, there is potential for increasing productivity by reducing excessive firm size or production capacity, which was unnecessarily expanded during the boom period.

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

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Appendix A

A.1. DEA models and slacks

A.1.1. Models for DEA with continuous variables

Input-oriented CRS and VRS models are used in this study to measure the efficiency of DMUs, using only continuous variables of the production process. We assume that there are n DMUs which produce s outputs, $\mathbf{y} \in R_S^+$ by using m inputs, $\mathbf{x} \in R_m^+$. Then the technical efficiency of DMU k under the CRS assumption can be evaluated by solving the following linear programming problem:

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

where θ_k^c is the objective function's value; ε is a non-Archimedean infinitesimal, 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 *i*th input of firm j, where $i = 1, 2, \cdots, m$; y_{rj} is the *r*th 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 subscript k indicates the DMU k. We hereafter refer to the model shown in equation (A1) as the CRS-DEA model.

If the value of an optimal objective function of DMU k, θ_k^c, is equal to unity and all input and output slack variables are equal to zero, then enterprise k is CRS-efficient and the firm is operating on the CRS frontier. In such a case enterprise k is regarded as fully utilizing its inputs in producing outputs. Otherwise, if θ_k^c is not equal to (equivalently, less than) unity and/or some of the slacks have non-zero values, then enterprise k is not CRS-efficient. In this case some resources are still being over-utilized. The inefficiency may be caused by improper or inefficient harmonization of resources in the enterprise, which can eliminate the inefficiency through benchmarking on the production frontier. 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 the technical efficiency of enterprise k.

In the CRS-model shown in equation (A1) DMUs operating on the best-practice frontier represent both technical efficiency and scale efficiency, which implies that all of them are producing their outputs at the Most Productive Scale Size (MPSS) (Banker and Morey, 1986a). Since this assumption is too strong to impose in practice, a more flexible assumption is needed to allow 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. We denote the VRS technical efficiency as θ_k^v.

The 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 the scale efficiency of enterprise k is unity, then the enterprise is regarded as scale efficient. Then, only enterprises having a unit value of scale efficiency are operating at 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 scores are not equal, then $\sum_{j=1}^{n} \lambda_j < 1$ indicates IRS whilst $\sum_{j=1}^{n} \lambda_j > 1$ indicates DRS.

A.1.2 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 a nonlinear programming problem and is called imprecise DEA (IDEA) (Cooper et al., 1999). Since this nonlinear programming requires special computational codes for each evaluation, an alternative algorithm for converting this nonlinear programming to the linear form is required. This nonlinear programming can be easily converted to the linear programming as suggested by Zhu (2004).[8] We employ a model found in 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. An output set is divided into two sets, each of which 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

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

or to simplify the presentation,

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

$$y_{r1} \le y_{r2} \le \cdots \le y_{r,k-1} \le y_{rk} \le y_{r,k+1} \le \cdots \le y_{rn}, \quad r \in DO$$

$$x_{i1} \le x_{i2} \le \cdots \le x_{i,k-1} \le x_{ik} \le x_{i,k+1} \le \cdots \le x_{in}, \quad i \in DI. \tag{A4}$$

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

$$\min \quad \theta_k^i - \varepsilon\left(\sum_{i \notin DI} S_i^- + \sum_{i \in DI} S_i^- + \sum_{i \notin DO} S_i^+ + \sum_{i \in DO} S_i^+\right)$$

$$s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta_k x_{ik}, \quad i \notin DI$$

$$\sum_{j \neq o} \lambda_j \overline{x}_{ij} + \lambda_k \underline{x}_{ik} + S_i^- = \theta_k \underline{x}_{ik}, \quad i \in DI$$

$$\sum_{j=1}^{n} \lambda_j y_{ij} - S_r^+ = y_{rk}, \quad r \notin DO$$

$$\sum_{j \neq o} \lambda_j \underline{y}_{rj} + \lambda_k \overline{y}_{rk} - S_i^+ = \overline{y}_{rk}, \quad i \in DI$$

$$\theta_k^v,\ \lambda_j,\ S_i^-,\ S_r^+ \ge 0, \tag{A5}$$

where the bar under the symbol indicates the lower bound of the corresponding ordinal variable and the bar above the 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 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 linear programming with a set of exact data.

A.2. Technical efficiency in previous studies

Using DEA-related approaches, the technical efficiencies of various industries can be measured. The Appendix Tables A1 and A2 summarize 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 different 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.

Appendix Table A1. Average technical efficiencies at firm-level in previous studies: Manufacturing industry

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 manufacturers, 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 parentheses represent output-oriented efficiency.
***Since the sample size is small, raw efficiencies are presented.

Appendix Table A2. Average technical efficiencies at firm-level in previous studies: Service industry

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 parentheses represent output-oriented efficiency.

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

Appendix Table A3. Model specification and Spearman's rank correlation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output							
Sales growth	○	○	○		○		
Labor productivity	○	○		○		○	
Innovation income	○		○	○			○
Spearman's ρ	-	0.527	0.482	0.529	-0.149	0.530	0.485

Note:
(1) ○ denotes a variable included in the specification.
(2) Numbers in the last row represent Spearman's rank correlation coefficient between technical efficiency scores of the model specified in each column and technical efficiencies of model (1).