

Badunenko, Oleg; Grechaniuk, Bogdana; Talavera, Oleksandr

**Working Paper**

## Development under Regulation: The Way of the Ukrainian Insurance Market

DIW Discussion Papers, No. 644

**Provided in Cooperation with:**

German Institute for Economic Research (DIW Berlin)

*Suggested Citation:* Badunenko, Oleg; Grechaniuk, Bogdana; Talavera, Oleksandr (2006) : Development under Regulation: The Way of the Ukrainian Insurance Market, DIW Discussion Papers, No. 644, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin

This Version is available at:

<https://hdl.handle.net/10419/18537>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

**Discussion Papers**

**DIW Berlin**

German Institute  
for Economic Research

**644**

**Oleg Badunenko  
Bogdana Grechanyuk  
Oleksandr Talavera**

**Development under Regulation:  
The Way of the Ukrainian Insurance Market**

**Berlin, November 2006**

Opinions expressed in this paper are those of the author and do not necessarily reflect views of the institute.

IMPRESSUM

© DIW Berlin, 2006

DIW Berlin

German Institute for Economic Research

Königin-Luise-Str. 5

14195 Berlin

Tel. +49 (30) 897 89-0

Fax +49 (30) 897 89-200

<http://www.diw.de>

ISSN print edition 1433-0210

ISSN electronic edition 1619-4535

Available for free downloading from the DIW Berlin website.

# Development under regulation: the way of the Ukrainian insurance market

Oleg Badunenko, Bogdana Grechanyuk, and Oleksandr Talavera\*

August, 2006

---

\* Badunenko: Department of Economics, European University Viadrina, Große Scharrnstr. 59, Frankfurt (Oder), 15230, Germany, Phone: +49(0)33555342946, Fax: +49(0)33555342959, e-mail: [badunenko@uni-ffo.de](mailto:badunenko@uni-ffo.de); Grechanyuk: Ostrog Academy, Seminarska Street 2, Ostrog, Rivnenska region, Ukraine, 35800, Phone +380505734118, email: [bogdanka@oa.net.ua](mailto:bogdanka@oa.net.ua); Talavera: German Institute for Economic Research (DIW-Berlin), Königin Luise Str. 5, Berlin, 14195, Germany, Phone: +49(0)3089789 407, Fax: +49(0)3089789 104, e-mail: [otalavera@diw.de](mailto:otalavera@diw.de).

# Development under regulation: the way of the Ukrainian insurance market

**Abstract.** This study is intended to assess the introduction of increased capitalization requirements for Ukrainian insurance firms. To do so, we employ up-to-date frontier efficiency analysis. The analysis suggests that an increase in size occurs not only because of the regulator's requirements, but also because *all* scale inefficient firms have been persistently operating under increasing returns to scale. Additionally, we show that the Ukrainian insurance industry experiences significant increases in technical efficiency. Our analysis identifies winners and losers among small, medium and large companies. The findings are consistent with the hypothesis that regulation forces firms to concentrate on efficiency.

**Key words:** insurance industry, efficiency and productivity analysis, returns to scale, bootstrap, Ukraine

**JEL Classification:** G22, G28, C15

## **1 Introduction**

Currently one of the hot topics in practices of financial market services is the issue of regulation, which aims at consolidation/strengthening of insurance market. This issue gains more and more attention since it has both positive and negative effects on the state of the insurance industry as a whole. On the one hand, such regulation facilitates eliminating small and inefficient firms from the market. However, on the other hand, it enables firms to develop in terms of “blind” growth, while little attention is paid towards improving efficiency.

In recent issues of this *Journal*, Cummins and Rubio-Misas (2006) analyze the effects of the introduction of the European Union’s Third Generation Insurance Directives on the Spanish insurance market. In an attempt to make legislation and the economy closer to those of the European Union, a regulatory institution of a large transitional country, Ukraine, has issued an amendment to the “Law about Insurance”, which is set to make the Ukrainian insurance market stronger. Following the recommendations of the Ministry of Finance and the World Bank, the regulator has increased the requirements of capitalization of the insurance firm in the first quarter of 2003. Among some 350 firms operating on the market, immediately following the introduction of the new policies, more than 50 could not cope with the increased requirements. Analysts consider that turning from quantity to quality of the Ukrainian insurance firm is the correct step in the improvement of providing insurance services. Moreover, this change in legislation is set to stop outsourcing capital abroad, which weakens that entire economy. Nevertheless, some small serious firms are forced to leave the market. In what follows, we test the hypothesis that the regulator is interested in achieving long-term goals, such as the establishment of a strong insurance market, instead of short-term goals, such as instant growth.

The objective of this study is to assess the effects of the introduction of a new law with the help of modern efficiency and productivity measurement techniques, more specifically, using Data Envelopment Analysis (DEA) and the Malmquist approach to decomposition of change in total factor productivity. We employ these methodologies to about 160 Ukrainian insurance companies during 2003–2005. Our main findings

suggest that increased capitalization requirements have positively influenced the Ukrainian insurance market and helped improve both technical and scale efficiency. In particular, the number of small firms has significantly decreased. Furthermore, the technical efficiency improvement is observed among *all* insurance companies, regardless of size. This outcome holds even during such political shocks as a presidential election and Ukraine's "Orange" revolution associated therewith. The results also suggest that *all* scale inefficient firms are inefficient because they operate on an increasing returns to scale portion of the global technology. Finally, the insurance industry faced a positive and relatively large scale efficiency improvements, which is mostly observed among small- and medium-sized firms.

The remainder of this paper is organized as follows: Section 2 provides background information on similar researches in developed countries; Section 3 describes the modern techniques used in this paper; Section 4 presents the empirical results; and finally Section 5 summarizes and concludes the study.

## **2 Background**

Despite the practical value of studying financial performance in the insurance industry, our paper is the first to examine such performance in the Ukrainian insurance market. Nevertheless, there are a number of studies on efficiency in the insurance industry for developed countries.

For example, the U.S. insurance market is investigated by Cummins and Zi (1998), Cummins *et al.* (1999). The first study compares cost efficiency estimates of U.S. life insurance using a range of econometric and mathematical programming methodologies.<sup>1</sup> The results indicate that the choice of estimation methodology makes a serious difference in terms of the estimated cost efficiency value. The second study examines the relationship between acquisitions and efficiency in the U.S. life insurance industry.

Hardwick (1997) analyzes the UK life insurance industry, particularly the level of its economic inefficiency, economies of scale and effects of the formation of the European

---

<sup>1</sup> See also this paper for an extensive review of the application of frontier efficiency methodologies in insurance.

single market. Shiu (2004) empirically defines the determinants of UK general insurance company performance. Cummins and Rubio-Misas (2006) have analyzed the role of consolidation and deregulation on the Spanish insurance industry. The study is focused on estimating the effect of the European Union's Third Generation Insurance Directives (1994) and the policy of the Spanish government during the 1980's on changes in the structure of the Spanish insurance market. The authors also determine whether the consolidation has removed inefficient and poorly performing firms from the market and estimated the total factor productivity growth. In the Spanish insurance industry, the role of organizational form is analyzed by comparing stock and mutual insurers (Cummins et al. 2004). Mahlberg and Url (2003) study the effects of liberalization on technical efficiency and the productivity development of the Austrian insurance industry. Finally, Adams and Buckle (2003) focus on the insurance market of the offshore financial centre (Bermuda) and define the determinants of corporate financial performance in this market.

All of these studies investigate attempts to quantify efficiency in developed countries, where regulation is likely to have the desired effect. On the other hand, we recognize that the effects of regulation in transition countries could be completely unanticipated, especially during political turmoil like the "Orange revolution".

### **3 Methodology**

An assessment of technical efficiency of firms requires measuring the best practice frontier and identifying a point of reference for judging the relative efficiency level of the unit under inspection. In this paper, the best practice frontier is estimated as the upper boundary of the smallest convex free disposable cone of the observed data on inputs and outputs using the data envelopment analysis (DEA) estimator (DEA is initiated by Charnes *et al.* (1978); see Kneip *et al.* (1998) for a proof of consistency for the DEA estimator, as well as Kneip *et al.* (2003) for its limiting distribution). The reason for opting this non-parametric mathematical programming technique in favor of parametric statistical approaches is two-fold. Firstly, DEA is particularly advantageous in analysis of the insurance industry, which allows not only for measuring technical efficiency, but also for conveniently looking at the development of both efficiency and productivity over time



(see Cummins and Rubio-Misas 2006). Secondly, newly developed bootstrap procedures enable retrieval of statistical properties of efficiency estimates, thereby furthering previously available point estimates to rigorous hypotheses testing (Simar and Wilson 1998, 2000b; Simar and Zelenyuk 2003).

One of the *a priori* assumptions which has to be made before employing DEA is the assumption about the returns to scale of the underlying technology. Literature suggests that different returns to scale assumptions result in completely different conclusions (see discussion and empirical application in Färe *et al.* [1994] and Ray and Desli [1997]). Fortunately, a reliable bootstrap procedure has already been developed which puts forward a direct data driven test of the returns to scale (Simar and Wilson 2002). Authors suggest a technique not only to test for global returns to scale, but also to test for the returns to scale at which a particular decision making unit is operating (known as a scale efficiency), and, if the unit is not scale efficient, the test for judgment at which portion of technology the unit is operating: increasing or decreasing returns to scale.

DEA allows two orientation choices which reflect underlying technology. The first is output orientation, which fixes inputs on the observed level and boosts outputs as much as possible within best-practice technology. The second is input orientation, which, holding outputs constant, tries to decrease inputs within best-practice technology. In the analysis of manufacturing firms one would surely be interested in output orientation, since resources are limited and not subject to very rapid change, and the economic purpose is to produce as much as possible. In the insurance industry, which represents the services sector, the maximum of output is naturally restricted by the amount of services that an insurance firm can possibly grant. For this reasoning and in line with the literature (e.g., Cummins and Rubio-Misas 2006) we stick to input orientation in our analysis.

### **3.1 Technical efficiency**

For each firm  $j$  ( $j=1,\dots,K$ ) vector  $x_j = (x_{j1}, \dots, x_{jN}) \in \mathfrak{R}_+^N$  denotes  $N$  inputs, vector  $y_j = (y_{j1}, \dots, y_{jM}) \in \mathfrak{R}_+^M$  denotes  $M$  outputs. We assume that under technology  $T$  outputs are producible by inputs,

$$T = \{(x, y) : y \text{ is producible by } x\} \quad (1)$$

For input-based scores of technical efficiency the technology is represented by its input requirement set,

$$L(y) \equiv \{x : (x, y) \in T\} \quad (2)$$

The Shephard's (1970) input distance function is defined as

$$D_j^i(y_j, x_j) = \sup \left\{ \theta : \frac{x}{\theta} \in L(y) \right\} \quad (3)$$

This function by construction is greater or equal than unity, and is convenient in the sense of providing information about the amount of necessary contraction of inputs to move a firm to a boundary or input requirement set. The Farrell's type of technical efficiency is measured by the reciprocal of Shephard distance function, and is given by

$$TE_j^i = \min \left\{ \theta : \theta x \in L(y) \right\} = \frac{1}{D_j^i(y_j, x_j)} \quad (4)$$

Technical efficiency is calculated via the activity analysis model, and for each firm  $j$  also is computed solving linear programming program:

$$\hat{\theta}_j = \min \left\{ \theta : y_j \leq \sum_{i=1}^K z_i y_i, \theta x_j \geq \sum_{i=1}^K z_i x_i; \theta \geq 0, z_i \geq 0, i = 1, \dots, K \right\} \quad (5)$$

This version of DEA calculates constant returns to scale efficiencies. Other returns to scale can be modeled by adjusting intensity variables  $z_i$ 's (see Färe *et al.* 1994a for details).

### 3.2 Bias corrected technical efficiency

Although the DEA method is typically considered to be deterministic, the efficiency is still computed relative to *estimated* and not to *true* frontier. The efficiency scores obtained from a finite sample (for example, in equation (5) from  $K$  observations) are subject to sampling variation of the *estimated* frontier (Simar and Wilson 1998). What is claimed is that *estimated* technical efficiency measures are too optimistic due to the fact

that the DEA estimate of the production set is necessarily a weak subset of the true production set under standard assumptions underlying DEA. It is proposed that the following bootstrap algorithm enables retrieval of bias-corrected estimates of original (as in equation(5)) “overstated” technical efficiencies:

(1.1) Obtain efficiency scores  $\hat{\theta}_j$  as in (5) for each firm  $j, j=1, \dots, K$ .

(1.2) Using a smooth bootstrap, generate a random sample of size  $K$  from  $\hat{\theta}_j, j=1, \dots, K$ ;  $\theta_{1b}^*, \dots, \theta_{Kb}^*$ , where

$$\theta_j^* = \bar{\beta}^* + \frac{1}{\sqrt{1 + h^2 / \hat{\sigma}_\theta^2}} (\tilde{\theta}_j^* - \bar{\beta}^*) \quad (6)$$

$$\tilde{\theta}_j^* = \begin{cases} \beta_j^* + h\varepsilon_j^* & \text{if } \beta_j^* + h\varepsilon_j^* \leq 1, \\ 2 - \beta_j^* - h\varepsilon_j^* & \text{otherwise.} \end{cases} \quad (7)$$

$\beta_1^*, \dots, \beta_K^*$  is a bootstrap sample from original efficiency estimates as in step (1.1),  $h$  is the smoothing parameter of the kernel density estimate of original efficiency estimates, and  $\varepsilon_j^*, j=1, \dots, K$  are random draws from the standard normal.

(1.3) Compute  $x_{jb}^*$  for each  $j, j=1, \dots, K$ ,

$$x_{jb}^* = \frac{\hat{\theta}_j}{\theta_{jb}^*} x_j \quad (8)$$

(1.4) Compute the bootstrap estimate  $\hat{\theta}_{jb}^*$  of  $\hat{\theta}_j$  for each  $j, j=1, \dots, K$ , by solving linear programming problems

$$\hat{\theta}_{jb}^* = \min \left\{ \theta : y_j \leq \sum_{i=1}^K z_i y_i, \theta x_j \geq \sum_{i=1}^K z_i x_{ib}^*; \theta \geq 0, z_i \geq 0, i = 1, \dots, K \right\} \quad (9)$$

Repeat steps (1.2) to (1.4)  $B$  times to obtain estimates  $[\hat{\theta}_{jb}^*, b=1, \dots, B]$  for each  $j, j=1, \dots, K$ . Bias-corrected estimates of original technical efficiency from equation (5) are

$$\tilde{\theta}_j = \hat{\theta}_j - \hat{bias}_j \quad (10)$$

$$\hat{bias}_j = \frac{1}{B} \hat{\theta}_{jb}^* - \hat{\theta}_j \quad (11)$$

### 3.3 Weighted technical efficiency

The number of firms is large, and it would be cumbersome to trace the performance of each individual firm. Therefore, in our analysis we will also look at the performance of an average representative firm. As shown by Färe and Zelenyuk (2003) the simple averages of technical efficiency scores are misleading and weighted averages have to be adopted instead. Since we do not have data on output prices, we rely on the price independent weights, which are the sum of each firm's share of each output normalized by the number of outputs M:

$$w_j = \frac{1}{M} \left( \frac{y_{j1}}{\sum_{i=1}^K y_{i1}} + \frac{y_{j2}}{\sum_{i=1}^K y_{i2}} + \dots + \frac{y_{jM}}{\sum_{i=1}^K y_{iM}} \right) = \frac{1}{M} \sum_{m=1}^M \frac{y_{jm}}{\sum_{i=1}^K y_{im}} \quad (12)$$

for each  $j, j=1, \dots, K$ .

### 3.4 Non-parametric test of returns to scale

Simar and Wilson (2002) suggested a non-parametric test of returns to scale. Their idea of testing the null hypothesis that technology is globally *constant* returns to scale versus the alternative hypothesis that technology is globally *variable* returns to scale boils down to testing to what extent the potential test statistic is different from its bootstrap analogue. The measure of scale efficiency, originally proposed by Färe and Grosskopf (1985),

$$s_j(y_j, x_j) = \frac{D_j^{CRS}(y_j, x_j)}{D_j^{VRS}(y_j, x_j)} \quad (13)$$

is used to facilitate the bootstrap test. Among others, the test statistic, which showed the best statistical properties, is defined as

$$\hat{S}_{2n}^{CRS} = \frac{\sum_{j=1}^K \hat{D}_j^{CRS}(y_j, x_j)}{\sum_{j=1}^K \hat{D}_j^{VRS}(y_j, x_j)} \quad (14)$$

If the null hypothesis is true, then  $\hat{D}_j^{CRS}(y_j, x_j) = \hat{D}_j^{VRS}(y_j, x_j)$   $j=1, \dots, K$ , and  $\hat{s}_j = 1$ . If the alternative hypothesis is true, then  $\hat{s}_j < 1$ . Since  $\hat{S}_{2n}^{CRS} \leq 1$ , the null hypothesis is rejected if  $\hat{S}_{2n}^{CRS}$  is significantly less than unity.

Taking into account the importance of returns to scale assumption for DEA results, this data-driven test is advised to be performed before applying any DEA model. Additionally, this test can be easily translated to hypothesis testing by individuals. The CRS assumption is only feasible when all firms are operating at an optimal scale; i.e., when scale elasticity is unity. However, for many reasons (e.g., imperfect competition, financial constraints) it is more appropriate to assume variable returns to scale (see Coelli *et al.* (2002) for the history and development of this stream). Assuming CRS when VRS should be assumed in reality mixes up technical efficiency estimates exactly by scale efficiencies. Therefore, performing the individual returns-to-scale test is fairly important in the case of scale efficiency analysis. The testing procedure is the following.

Under the null hypothesis that distance functions are equal under constant and variable returns to scale,  $s_j(y_j, x_j) = 1$ . Since by definition  $s_j(y_j, x_j) \leq 1$ , such a null hypothesis is rejected if  $s_j(y_j, x_j)$  is significantly less than unity; this test is performed for each  $j, j=1, \dots, K$ . For firm  $j$ , for which this null hypothesis is rejected,  $s_j(y_j, x_j) < 1$  and this firm is found to be scale inefficient. Hence, a further test has to be performed. With another measure of scale inefficiency, defined as

$$\eta_j(y_j, x_j) = \frac{D_j^{NIRS}(y_j, x_j)}{D_j^{VRS}(y_j, x_j)} \quad (15)$$

and which is less or equal to unity by construction, the test concludes that a firm is operating under increasing returns to scale if  $\eta_j(y_j, x_j)$  is significantly less than unity and is operating under decreasing returns to scale otherwise.

All tests in this subsection are bootstrap tests, built on prior works by Simar and Wilson (1998; 2000a), and we do not describe them in detail to conserve space. Interested readers are referred to the original paper by Simar and Wilson (2002).

### 3.5 Productivity growth analysis

As in original work by Grosskopf (1993), we refer to a change in efficiency and technology as productivity growth. The change in efficiency shows by how much the distance to the frontier changed between two periods. The change of technology shows to what extent the frontier itself changed. Similarly to Cummins and Rubio-Misas (2006) we will do a productivity analysis using Malmquist productivity indices (MPI). In addition to (3), in order to define such indices we need definitions of distance functions with different reference time periods (here and further in the definitions superscript  $b$  stands for base, while superscript  $c$  stands for current period):

$$D_j^b(y_j^c, x_j^c) = \sup \left\{ \theta : \frac{x^c}{\theta} \in L(y^b) \right\} \quad (16)$$

and

$$D_j^c(y_j^b, x_j^b) = \sup \left\{ \theta : \frac{x^b}{\theta} \in L(y^c) \right\} \quad (17)$$

The distance function in (16) measures the maximum proportional change in inputs of current period so that  $(x_j^c, y_j^c)$  is feasible in terms of base technology. Similarly, the distance function in (17) measures the maximum proportional change in inputs of base period so that  $(x_j^b, y_j^b)$  is feasible in terms of current technology. With definitions (16) and (17) in mind the input-based Malmquist indices relative to base and current technologies are, respectively,

$$M_j^b = \frac{D_{CRS}^b(y_j^b, x_j^b)}{D_{CRS}^b(y_j^c, x_j^c)}, \quad M_j^c = \frac{D_{CRS}^c(y_j^b, x_j^b)}{D_{CRS}^c(y_j^c, x_j^c)} \quad (18)$$

Following the approach of Färe, *et al.* (1994b) we adopt “Fisher ideal” decomposition, based on geometric average of two measures, which gives us two desired components: (i) change of efficiency (*EFF*) and (ii) change of the technology (*TECH*):

$$M(x^c, y^c, x^b, y^b) = \left[ \frac{D_{CRS}^b(y_j^b, x_j^b)}{D_{CRS}^c(y_j^c, x_j^c)} \right] \times \left[ \frac{D_{CRS}^c(y_j^c, x_j^c) D_{CRS}^c(y_j^b, x_j^b)}{D_{CRS}^b(y_j^c, x_j^c) D_{CRS}^b(y_j^b, x_j^b)} \right]^{\frac{1}{2}} =: EFF \times TECH \quad (19)$$

The decomposition in (19) applies if one believes the underlying technology is constant returns to scale. However if variable returns to scale is in turn adopted, then Malmquist index can be decomposed into three components: (i) change of efficiency (*EFF*) and (ii) change of the technology (*TECH*), and (iii) scale change (*SCALE*):

$$\begin{aligned} M(x^c, y^c, x^b, y^b) &=: EFF \times TECH \times SCALE \\ EFF &= \frac{D_{VRS}^b(y_j^b, x_j^b)}{D_{VRS}^c(y_j^c, x_j^c)} \\ TECH &= \left[ \frac{D_{VRS}^c(y_j^c, x_j^c) D_{VRS}^c(y_j^b, x_j^b)}{D_{VRS}^b(y_j^c, x_j^c) D_{VRS}^b(y_j^b, x_j^b)} \right]^{\frac{1}{2}} \quad (20) \\ SCALE &= \left[ \frac{D_{CRS}^b(y_j^b, x_j^b) D_{VRS}^c(y_j^c, x_j^c) D_{CRS}^c(y_j^b, x_j^b) D_{VRS}^b(y_j^c, x_j^c)}{D_{VRS}^b(y_j^b, x_j^b) D_{CRS}^c(y_j^c, x_j^c) D_{VRS}^c(y_j^b, x_j^b) D_{CRS}^b(y_j^c, x_j^c)} \right]^{\frac{1}{2}} \end{aligned}$$

The choice of the benchmark technology is akin to choosing between decomposition (19) and decomposition (20). This is where the usefulness of subsection (3.4) comes up. We are not going to base this choice on a belief, but rather first test for the returns to scale of the underlying technology and only then start the analysis. Moreover, instead of using original technical efficiencies as in equation (5), we employ bias corrected technical efficiencies as described in the subsection (3.2).

### 3.6 Aggregation of Malmquist productivity Indexes

Building on the idea of Färe and Zelenyuk (2003), Zelenyuk (forthcoming) showed that simple arithmetic or geometric averages are misleading in showing an “average” effect of components of Malmquist productivity indexes. He lays a theoretical foundation

for aggregating the MPI and its decompositions. Instead of relying on equally-weighted averages the following price independent weights are proposed:

$$\tilde{S}_j^\tau = \sum_{m=1}^M a_{\tau m} \bar{w}_{j\tau m} \quad (21)$$

for each  $j, j=1, \dots, K.$ , where

$$\bar{w}_{j\tau m} = \frac{y_{jm}^\tau}{\bar{Y}_{jm}} \quad (22)$$

is the share of  $j$ 's firm in terms of output  $M$ . Since the information is unavailable, we follow the recommendation of the author to assume  $a_{\tau m}$  to be constant for all outputs.

## 4 Empirical results

In this section we present our main findings. We start with data description and then turn to discussion of returns to scale, under which the insurance industry has been operating, as well as to examination of efficiency estimates. Finally, we assess productivity changes in the industry.

### 4.1 Data

The data come from [www.insurancetop.com](http://www.insurancetop.com) compiled for 163 firms providing insurance services in the Ukrainian market in different years. Unbalanced quarterly panel covers periods from the second quarter of 2003 to the first quarter of 2005. The data represent firms involved in different insurance activities. Unfortunately, the resource does not allow for differentiation between various types of firm's insurance pursuits. This can be seen as the major drawback of the data; however, as of this writing, the data covers a representative portion of the insurance market in Ukraine and provides the largest available panel. Furthermore, the complete and consistent data, which we use in analysis, are available only for four quarters: 2003q2, 2003q3, 2004q3, and 2005q1.

Along the lines of the literature (e.g., Cummins and Zi 1998, Fecher *et al.* 1992, Fecher and Pestieau 1993, Grigorian and Manole 2002, and Sherman and Gold 1985), we use inputs and outputs to characterize an operational process of firms. The outputs of insurance firms are represented by the services they provide to customers; more



specifically, outputs are measured by various types of premiums, such as personal, property, liability etc. As for the inputs, we use two concepts pertaining to the insurance industry analysis. The first concept includes equity and liabilities. The second employs fixed and current assets. Equity is an important input for insurance firms since insurers maintain it to back the promise to pay claims even if losses exceed expectations and also to satisfy regulatory requirements. Liabilities provide another source of funds: borrowed funds and funds owed to reinsurers. While equity and liabilities represent financial capital of insurers, fixed assets represent physical capital of firms (book value of physical capital), and current assets represent long-term and current investments, cash and other assets.

<Please, insert Table 1 about here>

Table 1 shows the descriptive statistics for the sample of Ukrainian insurance companies. All monetary outputs and inputs are measured in thousands of Ukrainian national currency *hryvnya* (UAH), deflated by the respective consumer price index. Table 1 comprises statistics for the all available periods pooled together as well as statistics period by period. As a result of governmental requirements, the size of an average firm, measured by fixed assets, has been gradually and significantly increasing from 2,218 thousand by approximately 51 percent during a two-year period, while when measured by current assets—it increased from 36,596 thousand UAH by 123 percent during the same time in question. The average gross premiums for companies, measured in all available quarters are 26,522 thousand; at the same time, they have been increasing up to the third quarter of 2004 and then drop significantly in the first quarter of 2005. This phenomenon can credibly be explained by local political circumstances. First, the approaching presidential elections, a period known in business cycle theory as a “slow-down” phase. Secondly, the “Orange” revolution occurs in this period, bringing along with it macroeconomic uncertainty. Apparently, this tendency repeats for other premiums, because they are a part of gross premiums. Evidently, among different types of premiums, property premiums are the highest. This may be considered to be specific to a transitional economy with underdeveloped financial markets. Although the well-being of the population has improved recently, resulting in a higher demand for insurance services from population, still the largest part of premiums come from

business. The table with descriptive statistics also suggests that insurance firms are quite heterogeneous. The differential between the smallest and the largest firm is approximately 1,000 times. Table 1 also tells us that some companies have personal, liability, compulsory, and state payments of zero-value.

#### 4.2 Model selection

One of the caveats that should be emphasized in respect to these data is that they do not have information about employment? . Unfortunately, we cannot overcome this shortcoming<sup>2</sup> and instead have to rely on the statistical inference for deciding which model is appropriate and robust in our particular case from both statistical and economic points of view. To do so, we specify in total eight models and conduct a correlation analysis on obtained efficiency measures.

We employ two combinations of inputs: (i) fixed and current assets and (ii) liabilities and equity. On the output side we suggest four combinations of outputs, represented by various types of premiums received by a firm: (i) gross insurance premiums alone, (ii) personal, property, and liability insurance premiums, (iii) compulsory, state, and voluntary insurance premiums, and (iv) solely voluntary insurance premiums. Such permutations give us eight models (m1 to m8), which are summarized in the following table:

Table 2. Model specifications

Outputs \ Inputs	(y1) gross	(y2) personal, (y3) property, (y4) liability	(y5) compulsory, (y6) state, (y7) voluntary	(y7) voluntary
(x1) fixed, (x2) current	model 1 (m1)	model 2 (m2)	model 3 (m3)	model 4 (m4)
(x3) liabilities, (x4) equity	model 5 (m5)	model 6 (m6)	model 7 (m7)	model 8 (m8)

<sup>2</sup> We wrote a letter to firms in our sample, inquiring about the labor force, but the few replies were exceptions rather than representative of the situation.

For each period and for each model we perform a test for global returns to scale in order to determine which DEA model to employ (see methodological section 3.4). The results of the tests suggest that in almost all models technology is variable returns to scale. We cannot reject the null hypothesis that technology is globally constant returns to scale only for model m5 in quarter 2 of 2003 and for model m7 in quarter 3 of 2003. Further, we retrieve bias-corrected technical efficiency estimates using an algorithm described in methodological section 3.2. To conserve space we do not present here all efficiency estimates; they are, however available from the authors upon request as an Appendix B. Our goal now is to choose a model, which is used in further analysis. We do so by looking at the Spearman correlation coefficients between alternative specifications.

<Please, insert Table 3 about here>

Few observations are worth commentary. Firstly, Table 3 shows that in all but the second quarter of 2003 the correlation coefficients are remarkably high. In said period the lowest correlation is between models m3 and m8: 0.28. Secondly, the correlation is larger between models which use the same inputs: either between m1, m2, m3 and m4 (the first row of Table 2) or between m5, m6, m7 and m8 (the second row of Table 2). This observation is true for all periods under consideration. Therefore, for the robustness of the analysis we opt to stick to a single set of outputs, but have two different sets of inputs. This gives us four choices: (m1 and m5), (m2 and m6), (m3 and m7), or (m4 and m8). Thirdly, from the table it is not clear which model is homogeneously/uniformly correlated with the rest of models. We choose the set m2 and m6 for two reasons. First, it beats other pairs in terms of having a relatively stable correlation. Second, it uses the fullest set of output economically justifiable.

### **4.3 Technical efficiency**

Now that we know the appropriate technology, we apply homogeneous bootstrap as in Simar and Wilson (1998) to retrieve technical efficiency scores. Table 4 presents summary statistics of distribution of bias corrected technical efficiency period by period,

as well as for the whole sample. The averages of technical efficiency and number of firms by size categories<sup>3</sup> are shown in Table 5.

<Please, insert Table 4 about here>

<Please, insert Table 5 about here>

The most striking finding is that the Ukrainian insurance industry is fairly inefficient—inefficiency is about 40 percent in different years. This means that the same outputs could have been produced by about 60 percent of observed inputs if the inputs were employed with a frontier production technology. An eyeball test indicates that there is neither clearly decreasing nor clearly increasing tendency in performance of an “average” firm. In addition other parameters of the distribution of technical efficiency remained virtually unchanged. This implies that the “average” distance to the frontier stays the same during the period under inspection. Such behavior might stem from two considerations. First, both firms’ performance and technology remain unchanged. Second, firms’ performance has been increasing with the same speed as the improvement of technology. With the improvement of people’s welfare and increased demand for insurance services for both the population and for businesses, the first explanation is hardly convincing. Thus, firms are going hand in hand with technological improvement, but are always lagging behind technological change. In the literature the latter evidence is known as a “general purpose technology” argument, which emphasizes that it takes time before newly implemented technology can be utilized 100 percent efficiently (Helpman and Rangel 1999), and which explains continuous poor aggregate performance of Ukrainian insurance firms. Interestingly, the lower panel (results for Model 2) of Table 4 does not contradict the upper panel (results for Model 6), which proves this finding is robust.

Such visual inspection, however, cannot render rigorous conclusions as for gains or losses from changes in efficiency—the mean of the technical efficiency has been moving backwards and forwards greatly—from 50 to 60 percent in different years. We will scrutinize this issue in a later subsection of this study.

---

<sup>3</sup> Size categories are chosen as follows: firms with less than 4,000 of fixed assets are termed small, middle firms have fixed assets from 4,000 to 10,000, and firms with more than 10,000 of fixed assets are large.

We keep in mind that, according to legislation, firms have to increase their capitalization and they indeed have been doing so. We want to pay special attention to this increase. First we look at the performance of an “average” firm within different size categories. Table 5 reveals that according to results of Model 2 (upper panel) middle-sized firms have been operating with practically the same technical efficiency during the whole period under consideration. Moreover, the number of middle firms remains constant. This may be explained by the fact that legislation does not affect this size category. However, small and large firms have changed their performance. In the first two periods no changes occurred in either size category, but technical efficiency dropped in the third quarter of 2004, larger firms having lost more than smaller firms. This quarter is marked by uncertainty preceding the presidential election, which turned into the “Orange” revolution in the fourth quarter of 2004. After the uncertainty passed, the performance of small firms returned to the previous level, while larger firms did not recover.

Another observation worth noting is that the evolution of the number of firms is different within size categories. While the sum of number of middle and large firms remained just about the same (15, 15, 17, 18), the number of small firms decreased considerably. And since the performance of an “average” small firm has been stable, the regulation aimed at the elimination of small and weak firms has indeed been effective.

For a robustness check we did the same analysis for Model 6. The lower panel of Table 5 backs up the findings and conclusions made for Model 2. Moreover, with precision up to two decimal points, the results for three last quarters are identical.

In the two last quarters large firms operated worse compared to their smaller counterparts. Furthermore, if we look at the whole sample, small firms outperform large ones. If being small were more beneficial, why would firms still be interested in increasing their size? This puzzle is the subject of the next subsection.

#### **4.4 Scale efficiency**

We confirm that Ukrainian insurance industry has not been operating under constant returns to scale, which suggests the presence of scale inefficiency. In this subsection we

do a scale efficiency analysis following testing procedures for individual firms by Simar and Wilson (2002).

<Please, insert Table 6 about here>

Table 6 presents absolute and relative number of scale efficient firms, that is, firms for which Test 1 is not rejected. We first notice that the total number of firms has been decreasing over time. Transition from the second to third quarter of 2003 is accompanied by an increased number of scale efficient firms, but after that the number and the share of scale efficient firms have decreased until the portion returned to the level of the first quarter under consideration. However, the most noteworthy finding is that roughly half of firms are scale inefficient in different quarters. As a robustness check, we performed Test 1 for two different sizes of the test: 10 and 5 percent.

<Please, insert Table 7 about here>

Before we turn to the analysis of the remaining (scale inefficient) firms, let us look at the composition of scale efficient firms by size categories; the frequencies are given in Table 7. Most amazingly, *all* large firms are scale efficient in *all* observed periods. The increase in the share of scale efficient firms, which we noticed in Table 6 mostly stems from a jump in the share of small-scale efficient firms and their large number in comparison to middle firms, whose share plummeted. After the third quarter of 2003 the share of middle firms remained virtually the same, while the share of small firms dropped. All in all, these are small firms that are quite volatile in their performance and that have to gain more attention.

Finally, we aim at an examination of scale inefficient firms. Scale inefficient firms are those for which Test 1 is rejected. For these firms we do a Test 2, i.e., we want to find out on which portion of technology a certain firm operates: on decreasing or increasing returns to scale portion. If the null hypothesis of Test 2 (nonincreasing returns to scale, versus alternative, variable returns to scale) for a particular firm is rejected, it is then concluded that this firm is scale inefficient due to increasing returns to scale and has to exploit its fortune and increase in size. If the null hypothesis for a particular firm is not rejected, then decreasing returns to scale apply, and this firm has to decrease its size to become more scale efficient.

The most striking finding about performing Test 2 is that in *all* periods and for *all* firms, Test 2 is rejected. This result is backed by looking at scale inefficient firms, for which Test 1 is rejected with both a 10 and 5 percent size of the test. This robust outcome means that *all* scale inefficient firms strategically have to *increase* their size in order to become more scale efficient. We recall again that all large firms are scale efficient, thus illustrating the direction in which firms are heading.

This noteworthy finding tells us that the Ukrainian insurance industry has not been primarily seeking to improve its technical efficiency (we remember it has been staying nearly on the same level), but firms rather have made many efforts to establish an optimal scale. This is the evolution of a young, but promising industry, which has set the correct target. We note in our sample and also hear in the Ukrainian business news that the number of firms has decreased because some of them cannot cope with new capitalization requirements. These firms can be considered weak and have to leave the market, so that the remaining firms are involved in competition within a much stronger cohort. The strength of the insurance firm, among other factors, is measured by the capital or by size; so the newly introduced regulation goes hand in hand with the existing strategy of firms, and is correctly projected at strengthening the insurance market.

#### **4.5 The Malmquist Index**

Table 8 presents averages of Malmquist Productivity Indexes and their components by size categories together with number of firms in each respective category; the left-most panel shows MPI and components for the entire period, and from left to right three more adjacent periods comparisons, 2003q2–2003q3, 2003q3–2004q3, and 2004q3–2005q1. Recall the results of the test of returns to scale which reject global constant returns to scale technology, and so we acknowledge the presence of scale inefficiency and therefore the change of scale efficiency component should be present in the analysis. This leads to using decomposition (20) instead of decomposition (19). Simar and Wilson (1999) propose a bootstrap methodology for calculation of MPI. However, they correct components of index for bias, which is inferior to first correcting all distance functions for bias following Simar and Wilson (1998) and only then calculate components of decomposition. Another technical note is that not for all firms are all cross-time distance

functions feasible (Ray and Desli 1997); six observations in the whole sample, three in the 2003q2-2003q3 comparison, four in the 2003q3-2004q3 comparison, and fifteen observations in the 2004q3-2005q1 comparison are not feasible.

<Please, insert Table 8 about here>

The first noteworthy evidence in Table 8 is a quite significant loss in productivity during the whole sample—60 percent. This finding is backed by Model 6. When this productivity regress, however, is broken into subsamples, we clearly see that it is the last period, the “Orange” revolution, that is responsible for that. During the 2004q3-2005q1 (half year) comparison period, the Ukrainian insurance market lost 67 percent in productivity.<sup>4</sup> In the first 2003q2-2003q3 (one quarter) comparison period, the Ukrainian insurance industry experienced confident productivity growth—62 percent. In the next comparison period, 2003q3-2004q3 (one year), the productivity grew only 7.2 percent.

Additionally, the robust result confirmed by both models and by *all* periods comparisons that in the Ukrainian insurance industry change in efficiency has either contributed significantly to productivity growth or prevented productivity regress. This component is also a pure technical efficiency change, and Table 8 reveals that it is positive and significant—40 percent. This finding is unanticipated when taking into account the result of subsection 4.3. However, as we state there, only rigorous statistical procedures can tell the truth. Moreover, we note in footnote 4 that in the analysis of MPI we include only those firms into comparison which are observed in both periods and consequently do not look at firms exiting or entering the industry. Hence results from technical efficiency analysis (subsection 4.3) and from MPI analysis are not directly comparable. The only case of loss in technical efficiency is observed for large firms in the 2003q3-2004q3 comparison. This confirms previous findings in which weighted mean of technical efficiency of large firms dropped from 65 in the third quarter of 2003 to 47 percent in the third quarter of 2004.

Furthermore, the technology change component repeats the tendency of the productivity change. Seen throughout the whole sample, it is negative, but, during the

---

<sup>4</sup> One caveat should be stated, however. In the analysis on MPI, when we say market or industry, we really mean available in balanced sample firms, which is required by index construction.



first and second comparison periods, it identifies positive and large breakthroughs in technological development. It is in the last comparison, from 2004q3 to 2005q1, that technology dropped greatly. This plummeting can again be attributed to the uncertainty before presidential elections and associated with the aftermath of the “Orange” revolution.

What is of great importance for our analysis is the examination of changes in scale efficiency. Table 8 illustrates that it is positive throughout the whole sample, making up around 1.5 percent (1.8 percent from Model 6) thus indicating that introduced regulation proved effective. Aggregate scale efficiency growth occurs even despite the decline of share of scale efficient firms in the comparison of change from the third quarter of 2003 to the first quarter of 2005. Effectiveness of regulation is also proven as scale efficiency change was positive for small and middle firms when seen in the first and second comparisons. The third comparison, 2004q3–2005q1 is inconclusive, and furthermore changes the results for the whole sample to the opposite.

The results of MPI analysis are robust with respect to different model specification. Upper (Model 2) and lower (Model 6) panels of Table 8 reveal only minor numerical differences that do not alter our major conclusions. We recognize the presence of scale inefficiency during the period under consideration and its change proves positive. It implies that firms have been trying to adjust to the optimal scale at the same time improving technical efficiency, and indeed they have successfully been doing that, which is confirmed by positive and significant effects of scale efficiency change and technical efficiency change—26.5 and 8.4 percent and 13.1 and 5.7 percent during period 2003q2 to 2004q3, respectively.

## **5 Concluding remarks**

Although our methodology is superior to that used by Cummins and Rubio-Misas (2006), our data might be considered quite controversial. The data are useful in identifying the tendency of the production process, but are quite poor in providing additional information about the firm—such as organizational structure, type of insurance company *etc.* Secondly, the data is “jumpy” in the sense that the time space is

not the same between cross sections. Overcoming each of these warnings would improve the research greatly.

Nonetheless, we believe that our analysis manages to disclose an important tendency, which has occurred in the Ukrainian insurance industry during the period of the second quarter of 2003 up through the first quarter of 2005. In an attempt to economically eliminate weak and inefficient firms, the required level of capitalization was raised. It is supposed that less capital intensive firms are less flexible and, therefore, operate with more constraints. Tighter requirements became effective in 2003. We perform an efficiency and productivity analysis on insurance firms after the introduction of the regulation. The study suggests the following judgments about the change in legislation.

First, the number of firms has significantly decreased during the sample period. The composition of the industry has also been altered—whereas the number of middle and larger firms barely changed, the number of small firms has dropped by more than twenty percent. The size of the firm has increased considerably—by 51 percent measured by fixed assets, and by 123 percent measured by current assets.

Second, unlike the findings of Cummins and Rubio-Misas (2006), the efficiency improvement is significant—40 percent, the greatest improvement occurring among small firms, which are observed in all periods—44.3 percent. The efficiency improvement occurred even during the uncertainty concerning approaching presidential elections and the associated “Orange” revolution.

Third, not only legislation makes firms get bigger. The evidence suggests that *all* scale inefficient firms are inefficient because they have been persistently operating on the increasing returns to scale portion of the global technology. This implies that technology, and/or the market created favorable conditions for firms to increase in size up to an optimal level; regulation has merely formalized that.

Fourth, the insurance industry experiences a positive and relatively large scale efficiency improvement—1.5 percent. The majority of this improvement is observed within small and middle firms. This fact does not undermine the performance of large firms, since they *all* proved to be scale efficient in *all* periods.

We tested the hypothesis that the regulator's goal is long-term, and that it is aimed at strengthening the Ukrainian insurance market. The major conclusions of the study are that change in legislation is effective and that regulation indeed has the intended effect.

## 6 References

**Adams, M. and M. Buckle** (2003): "The Determinants of Corporate Financial Performance in the Bermuda Insurance Market." *Applied Financial Economics* **13**, 133-43.

**Charnes, Abraham; William W. Cooper and Edwardo L. Rhodes** (1978): "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research* **2**(6), 429-44.

**Coelli, Tim; D.S. Prasada Rao and George E. Battese** (2002): *An Introduction to Efficiency and Productivity Analysis*. London: Kluwer Academic Publishers.

**Cummins, J. David and Maria Rubio-Misas** (2006): "Deregulation, Consolidation, and Efficiency: Evidence from the Spanish Insurance Industry." *Journal of Money, Credit, and Banking* **38**(2), 323-55.

**Cummins, J. David; Maria Rubio-Misas and Hongmin Zi** (2004): "The Effect of Organizational Structure on Efficiency: Evidence from the Spanish Insurance Industry." *Journal of Banking and Finance* **28**(12), 3113-50.

**Cummins, J. David; Sharon L. Tennyson and Mary A. Weiss** (1999): "Consolidation and Efficiency in the U.S. Life Insurance Industry." *Journal of Banking and Finance* **2**(23), 325-57.

**Cummins, J. David and Hongmin Zi** (1998): "Comparison of Frontier Efficiency Methods: An Application to the U.S. Life Insurance Industry." *Journal of Productivity Analysis* **2**(10), 131-52.

**Färe, Rolf and Shawna Grosskopf** (1985): "A Nonparametric Cost Approach to Scale Efficiency." *Scandinavian Journal of Economics* **87**, 594-604.

**Färe, Rolf; Shawna Grosskopf and C. A. Knox Lovell** (1994a): *Production Frontiers*. Cambridge U.K.: Cambridge University Press.

**Färe, Rolf; Shawna Grosskopf; Mary Norris and Zhongyang. Zhang** (1994b): "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries." *American Economic Review* **84**(1), 66-83.

**Färe, Rolf and Valentin Zelenyuk** (2003): "On Aggregate Farrell Efficiencies." *European Journal of Operational Research* **146**, 615-20.

**Farrell, Michael J.** (1957): "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society. Series A (General)* **120**(3), 253-90.

**Fecher, Fabienne; Denis Kessler; Sergio Perelman and Pierre Pestieau** (1992): "Productive Performance of the French Insurance Industry." *Journal of Productivity Analysis* **4**(1-2), 77-93.

**Fecher, Fabienne and Pierre Pestieau** (1993): *Efficiency and Productivity Growth in Oecd Financial Services* in Harold O. Fried, C.A. Knox Lovell and Shelton S. Schmidt (ed.), *The Measurement of Productive Efficiency. Techniques and Applications*. Oxford: Oxford University Press, 374-85.

**Grigorian, David A. and Vlad Manole** (2002): "Determinants of Commercial Bank Performance in Transition: An Application of Data Envelopment Analysis," Policy Research Working Paper 2850, World Bank.

**Grosskopf, Shawna** (1993): *Efficiency and Productivity* in Harold O. Fried, C.A. Knox Lovell and Shelton S. Schmidt (ed.), *The Measurement of Productive Efficiency. Techniques and Applications*. Oxford: Oxford University Press, 160-94.

**Hardwick, Philip** (1997): "Measuring Cost Inefficiency in the Uk Life Insurance Industry." *Applied Financial Economics* **7**(1), 37-44.

**Helpman, Elhanan and Antonio Rangel** (1999): "Adjusting to a New Technology: Experience and Training." *Journal of Economic Growth* **4**, 359-83.

**Kneip, Alois; Byeong U. Park and Léopold Simar** (1998): "A Note on the Convergence of Non-Parametric DEA Estimators for Production Efficiency Scores." *Econometric Theory* **14**, 783-93.

**Kneip, Alois; Léopold Simar and Paul W. Wilson** (2003): "Asymptotics for DEA Estimators in Non-Parametric Frontier Models," Discussion Paper 0317, Institut de Statistique, Université Catholique de Louvain, Belgium.

**Mahlberg, Bernhard and Thomas Url** (2003): "Effects of the Single Market on the Austrian Insurance Industry." *Empirical Economics* **28**, 813–38.

**Ray, Subhash C. and Evangelia Desli** (1997): "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Comment." *American Economic Review* **87**(5), 1033-9.

**Shephard, Ronald W.** (1970): *Theory of Cost and Production Functions*. Princeton, N. J.: Princeton University Press.

**Sherman, H. David and Franklin Gold** (1985): "Bank Branch Operating Efficiency: Evaluation with Data Envelopment Analysis." *Journal of Banking and Finance* **9**, 297-315.

**Shiu, Yung-Ming** (2004): "Determinants of United Kingdom General Insurance Company Performance." *British Actuarial Journal* **10**(5), 1079-110.

**Simar, Léopold and Paul W. Wilson** (1998): "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models." *Management Science* **44**, 49-61.

\_\_\_\_\_ (1999): "Estimating and Bootstrapping Malmquist Indices." *European Journal of Operational Research* **115**, 459-71.

\_\_\_\_\_ (2000a): "A General Methodology for Bootstrapping in Non-Parametric Frontier Models." *Journal of Applied Statistics* **27**(6), 779-802.

\_\_\_\_\_ (2000b): "Statistical Inference in Nonparametric Frontier Models: The State of the Art." *Journal of Productivity Analysis* **13**, 49–78.

\_\_\_\_\_ (2002): "Non-Parametric Tests of Returns to Scale." *European Journal of Operational Research* **139**, 115–32.

**Simar, Léopold and Valentin Zelenyuk** (2003): "Statistical Inference for Aggregates of Farrell-Type Efficiencies," Discussion Paper 0324, Institut de Statistique, Université Catholique de Louvain, Belgium.

**Zelenyuk, Valentin** (forthcoming): "Aggregation of Malmquist Productivity Indexes." *European Journal of Operational Research*.

Table 1. Descriptive statistics for outputs and inputs: all data used in the analysis, and data by available quarters

Variable	N	Mean	St.D	Min	Max
All data					
x1	373	2665.5	5619.6	0.0	42275.6
x2	373	57010.7	120753.3	1000.5	896812.9
x3	373	38570.2	79157.7	826.4	714685.8
x4	373	21106.0	53568.6	197.9	490155.5
y1	373	26522.6	54255.1	404.5	459836.8
y2	373	1304.2	2611.2	0.0	20608.8
y3	373	20875.4	51731.9	62.9	456132.1
y4	373	1550.1	4490.2	0.0	55211.4
y5	373	2459.8	5048.7	0.0	32938.1
y6	373	349.7	3852.4	0.0	60649.7
y7	373	23713.1	52540.7	216.7	457734.3
2003q2					
x1	99	2218.1	5345.4	11.6	42275.6
x2	99	36596.2	83789.3	1000.5	743654.6
x3	99	23885.6	48582.3	826.4	382184.5
x4	99	14928.7	39158.5	197.9	361507.0
y1	99	18311.1	40216.1	432.9	338488.5
y2	99	945.5	1875.8	0.0	10569.3
y3	99	13732.2	37885.3	62.9	336045.6
y4	99	1629.8	6127.3	0.0	55211.4
y5	99	1759.2	3598.9	0.0	16882.5
y6	99	244.4	2335.2	0.0	23226.8
y7	99	16307.5	38982.4	216.7	336836.5
2003q3					
x1	96	2360.9	5392.4	0.0	41639.8
x2	96	44161.7	98738.1	1183.1	781746.9
x3	96	28627.5	56043.3	868.6	383441.8
x4	96	17895.1	46076.7	289.0	398339.4
y1	96	31296.6	61531.7	1051.9	459836.8
y2	96	1375.6	2718.3	0.0	16522.5
y3	96	24694.3	58953.6	69.7	456132.1
y4	96	2106.0	4902.2	0.0	28393.1
y5	96	2728.0	5794.2	0.0	32329.2
y6	96	392.7	3701.6	0.0	36257.6
y7	96	28175.9	59598.1	507.1	457734.3
2004q3					

x1	94	2821.1	5529.7	6.3	36997.4
x2	94	69518.8	141223.2	4219.0	896812.9
x3	94	47314.4	94062.2	2975.4	714685.8
x4	94	25025.6	65165.2	462.5	490155.5
y1	94	40617.5	71819.2	948.3	390995.6
y2	94	2014.4	3607.8	0.0	20608.8
y3	94	32723.1	69188.8	168.4	387299.0
y4	94	1858.4	3786.5	0.0	21649.5
y5	94	3355.5	5911.0	0.0	27586.4
y6	94	666.1	6256.0	0.0	60649.7
y7	94	36595.9	69828.1	531.7	387993.9
<hr/>					
2005q1					
x1	84	3367.0	6275.8	5.7	40991.8
x2	84	81758.0	148568.0	7204.5	889609.4
x3	84	57455.1	104732.8	6809.0	703206.5
x4	84	27669.9	61190.2	551.5	381054.0
y1	84	14971.9	26526.0	404.5	157920.0
y2	84	850.5	1556.9	0.0	7479.8
y3	84	11671.4	25209.3	86.0	153358.3
y4	84	475.9	907.8	0.0	5071.2
y5	84	1976.8	4422.6	0.0	32938.1
y6	84	70.9	577.7	0.0	5256.8
y7	84	12924.3	25595.3	226.1	157688.9

*Notes:* x1–fixed, x2–current assets, x3–liabilities, x4–equity, y1–premiums, y2–personal premiums, y3–property premiums, y4–liability premiums, y5–compulsory premiums, y6–state premiums, and y7–voluntary premiums.



Table 3. Spearman correlation coefficients between bias-corrected technical efficiency measures from alternative model specifications

2003q2								
	m1	m2	m3	m4	m5	m6	m7	m8
m1	1.00							
m2	0.77	1.00						
m3	0.93	0.67	1.00					
m4	0.93	0.83	0.79	1.00				
m5	0.43	0.48	0.44	0.36	1.00			
m6	0.46	0.70	0.37	0.51	0.74	1.00		
m7	0.37	0.37	0.41	0.27	0.96	0.68	1.00	
m8	0.35	0.54	0.28	0.45	0.75	0.88	0.69	1.00
2003q3								
	m1	m2	m3	m4	m5	m6	m7	m8
m1	1.00							
m2	0.83	1.00						
m3	0.91	0.67	1.00					
m4	0.93	0.87	0.77	1.00				
m5	0.71	0.55	0.67	0.63	1.00			
m6	0.63	0.75	0.48	0.66	0.81	1.00		
m7	0.65	0.44	0.70	0.51	0.93	0.69	1.00	
m8	0.71	0.68	0.57	0.75	0.92	0.89	0.78	1.00
2004q3								
	m1	m2	m3	m4	m5	m6	m7	m8
m1	1.00							
m2	0.92	1.00						
m3	0.85	0.72	1.00					
m4	0.97	0.95	0.76	1.00				
m5	0.66	0.60	0.56	0.64	1.00			
m6	0.51	0.59	0.34	0.56	0.84	1.00		
m7	0.61	0.53	0.67	0.56	0.91	0.74	1.00	
m8	0.61	0.63	0.42	0.66	0.92	0.91	0.81	1.00
2005q1								
	m1	m2	m3	m4	m5	m6	m7	m8
m1	1.00							
m2	0.87	1.00						
m3	0.93	0.88	1.00					
m4	0.96	0.90	0.90	1.00				
m5	0.88	0.79	0.83	0.85	1.00			
m6	0.79	0.85	0.78	0.80	0.92	1.00		
m7	0.79	0.70	0.83	0.73	0.92	0.84	1.00	
m8	0.83	0.80	0.78	0.87	0.96	0.94	0.85	1.00

Table 4. Technical Efficiency: Summary Statistics<sup>a</sup>

Period	N	Mean <sup>b</sup>	St.D	Coef. of Var	Skewness	Kurtosis	Min	Q25	Median	Q75
<b>Model 2</b>										
2003q2	99	0.58	0.23	0.48	-0.23	1.76	0.05	0.28	0.50	0.68
2003q3	96	0.60	0.22	0.44	-0.26	1.78	0.08	0.33	0.52	0.71
2004q3	94	0.50	0.19	0.43	-0.03	1.80	0.10	0.27	0.44	0.60
2005q1	84	0.56	0.24	0.45	-0.32	1.78	0.07	0.31	0.61	0.74
Total	373	0.56	0.22	0.46	-0.15	1.80	0.05	0.30	0.50	0.69
<b>Model 6</b>										
2003q2	99	0.62	0.21	0.44	-0.13	1.73	0.10	0.32	0.50	0.69
2003q3	96	0.61	0.22	0.44	-0.13	1.60	0.10	0.29	0.50	0.69
2004q3	94	0.60	0.20	0.38	-0.13	1.91	0.12	0.37	0.50	0.71
2005q1	84	0.60	0.24	0.43	-0.42	1.87	0.09	0.36	0.62	0.78
Total	373	0.61	0.22	0.43	-0.17	1.78	0.09	0.32	0.52	0.71

<sup>a</sup> Technical Efficiency are bias corrected due to Simar and Wilson (1998).

<sup>b</sup> Averages are due to Färe and Zelenyuk (2003).

Table 5. Averages<sup>a</sup> of Technical Efficiency and Number of Firms by Size Categories

**Model 2**

Size Category	Whole Sample		2003 q2		2003 q3		2004 q3		2005 q1	
	N	mean	N	mean	N	mean	N	mean	N	mean
Small	308	0.58	84	0.58	81	0.61	77	0.50	66	0.60
Middle	42	0.52	10	0.53	11	0.53	11	0.51	10	0.49
Large	23	0.55	5	0.63	4	0.65	6	0.47	8	0.49
Total	373	0.56	99	0.58	96	0.60	94	0.50	84	0.56

**Model 6**

Size Category	Whole Sample		2003 q2		2003 q3		2004 q3		2005 q1	
	N	mean	N	mean	N	mean	N	mean	N	mean
Small	308	0.64	84	0.63	81	0.61	77	0.50	66	0.60
Middle	42	0.55	10	0.57	11	0.53	11	0.51	10	0.49
Large	23	0.56	5	0.64	4	0.65	6	0.47	8	0.49
Total	373	0.61	99	0.62	96	0.60	94	0.50	84	0.56

<sup>a</sup> Averages are due to Färe and Zelenyuk (2003).

Table 6. Frequency of Scale Efficient firms<sup>a</sup>

Period	N	N of scale efficient firms	N of scale efficient firms, %	N of scale efficient firms	N of scale efficient firms, %
		The size of the test is 10 percent		The size of the test is 5 percent	
2003q2	99	46	0.46	51	0.52
2003q3	96	56	0.58	59	0.61
2004q3	94	45	0.48	51	0.54
2005q1	84	42	0.50	44	0.52

<sup>a</sup> The frequencies are identical for both Model 2 and Model 6.

Table 7. Frequency of Scale Efficient Firms by Size Categories<sup>a</sup>

Size Category	2003 q2		2003 q3		2004 q3		2005 q1	
	N	frequency	N	frequency	N	frequency	N	frequency
Small	84	0.44	81	0.58	77	0.48	66	0.44
Middle	10	0.90	11	0.73	11	0.73	10	0.70
Large	5	1	4	1	6	1	8	1
Total	99	0.52	96	0.61	94	0.54	84	0.52

<sup>a</sup> The size of the test assumed 5 percent; frequencies are identical for both Model 2 and Model 6.

Table 8. Mean values of Malmquist Productivity Indexes and its components by size categories<sup>a</sup>

	Whole sample					2003 q2 - 2003 q 3					2003 q3 - 2004 q 3					2004 q3 - 2005 q 1				
<b>Model 2</b>																				
Size Category	N	prod	eff	tech	scale	N	prod	eff	tech	scale	N	prod	eff	tech	scale	N	prod	eff	tech	scale
Small	40	0.408	1.443	0.404	0.959	58	1.637	1.038	1.308	1.301	47	1.022	1.038	1.195	1.150	40	0.328	1.205	0.398	0.672
Middle	3	0.748	1.112	0.476	1.270	10	1.650	1.195	1.220	1.348	11	1.247	1.253	1.097	1.022	8	0.393	1.464	0.375	0.728
Large	7	0.370	1.331	0.328	1.120	3	1.503	1.362	1.283	0.975	6	0.970	0.824	1.256	0.969	8	0.280	1.589	0.345	0.648
Total	50	0.407	1.400	0.384	1.015	71	1.620	1.131	1.279	1.265	64	1.072	1.057	1.180	1.084	56	0.330	1.347	0.381	0.678
<b>Model 6</b>																				
Size Category	N	prod	eff	tech	scale	N	prod	eff	tech	scale	N	prod	eff	tech	scale	N	prod	eff	tech	scale
Small	40	0.456	1.997	0.390	0.869	58	1.768	1.060	1.580	1.107	47	1.064	1.096	0.993	1.206	40	0.294	1.135	0.380	0.811
Middle	3	0.848	1.032	0.547	1.340	10	1.562	1.083	1.664	1.037	11	1.014	1.409	1.040	0.788	8	0.382	1.857	0.389	0.667
Large	7	0.568	1.235	0.467	1.326	3	1.534	1.065	1.985	0.755	6	0.916	0.860	1.177	0.934	8	0.316	1.388	0.366	0.653
Total	50	0.500	1.744	0.418	1.018	71	1.675	1.067	1.664	1.034	64	1.024	1.137	1.038	1.047	56	0.317	1.341	0.379	0.745

<sup>a</sup> Means are weighted averages due to Zelenyuk (forthcoming). Indexes and their components are based on distance functions, calculated using homogeneous bootstrap procedure by Simar and Wilson (1998). This procedure is superior to that of Simar and Wilson (1999) because it corrects not only components of indexes for biases, but also distance functions, which comprise the components.