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Comparing US State Health Efficiencies Employing Data Envelope Analysis

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Abstract

Over the past several decades, there have been improvements in health outcomes such as life expectancy, infant mortality rates and maternal mortality rates. Yet, the improvements in national health indicators often have not resulted in significantly reducing burdens of chronic disease among US citizens. Burden of disease studies examining population health employ assessments to measure chronic disease and disability burdens. We used the disability-adjusted life year (DALY) as the measure for overall disease burden. Our paper evaluates the efficiency of health care resources on a state-by-state population basis in the US by examining the 50 states through the application of a non-parametric method known as data envelope analysis (DEA). DEA allows multi-input and multi-output analysis. We conducted analyses to compare each state vis-à-vis the other states to examine the efficiency of the use of health resources in relation to disease burdens. We used three input variables-the number of physicians per 100,000 residents per state, the number of hospital beds per 1000 inhabitants per state and the public health funding per capita per state and one output variable- disability adjusted life years to reflect burden of disease. The study was conducted over a six-year duration (2008-2014). Our study demonstrates that there are varying levels of efficiency in the utilization of health resources (i.e. number of physicians, number of hospital beds and public health expenditures) among the 50 US states in affecting the output of disease burden. It appears that the Western US states and the northern most Midwest regions are the most efficient relative to the other states. The least efficient states were clustered in the south Midwestern region. The states showing the most improvement include the previously least efficient south-eastern states. This indicates that these south-eastern states are "catching up" or improving relative to the other states, but still have a large gap in efficiency utilization. The Western states with high efficiency also had higher use of technology. In contrast, the North-Midwestern states with high efficiency values had lower use of technology. This finding appears to show that these North-Midwestern states are efficient with their use of health resources, but their efficiency is not due to technological improvements as in the Western states.

Keywords: Data envelope; US health system; Population; Technology

Introduction

Over the past several decades, there have been improvements in health outcomes such as life expectancy, infant mortality rates and maternal mortality rates. Yet, the improvements in national health indicators often have not resulted in significantly reducing burdens of chronic disease among US citizens. Historically, mortality data was used for identifying the leading cause of health problems in a population [1]. While the causes of death remain important today, there is a greater emphasis to measure chronic diseases and disability. This is principally because mortality data does not fully measure the health of a population [2,3]. In contrast, burden of disease studies examining population health employ assessments to measure chronic disease and disability burdens [3]. These epidemiological and policy analyses often examine prevalence, incidence, premature death and years of life lost, as well as, direct monetary costs of medical care and indirect costs related to lost wages and productivity [4-6].

Burden of disease studies have been implemented in many countries using the disability of life year (DALY) to assess major health problems [3]. The disability adjusted life year was developed by the World Bank and the World Health Organization (WHO) to quantify the burden of disease and premature death [7-9]. Disability of adjusted life year is a summary measure of population health which reflects both the length of life lost to premature death as well as the time spent in unhealthy states [2,5,10].

There was a recent study conducted on the public health system efficiency of European countries. Asandului [11] shows that some of the developed European countries are efficient in output while using their healthcare inputs. Moreover, the study concludes that a dynamic approach using the Malmquist Index could be used to improve the study. To the best of our knowledge, few studies have examined the efficiency of resource utilization of the US health system comparing the 50 states using the Malmquist index.

Our paper evaluates the efficiency of health care resources on a state-by-state population basis in the US by examining the 50 states through the application of a non-parametric method known as data envelope analysis (DEA). DEA measures productivity efficiencies of decision making units (DMUs). In our paper, DMUs represent the states. DEA creates an efficiency frontier and compares all DMUs against the frontier. In addition, DEA is used to obtain a Malmquist productivity change index, which is a flexible, mathematical programming approach for the assessment of productivity through input and output variables [12,13]. DEA allows multi-input and multi-output analysis. We selected one output variable: disability adjusted life years as a measure to monitor health as a productivity factor. We selected three input variables: number of physicians per 100,000 residents per state, number of hospital beds per 1000 inhabitants per state and public health funding per capita per state. We conducted analyses to compare each state vis-à-vis the other states to examine the efficiency of the use of health resources.

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Methods

Data envelopment analysis

Data envelopment analysis can be defined a non-parametric technique that uses linear programming (lp) to compare the relative efficiencies of homogenous decision making units in transforming inputs into outputs. DEA was developed by Charnes [14], based on Farrell [15]. DEA uses lp models to build an efficiency frontier. The efficiency frontier is determined by the most efficient DMUs. Thus, the efficiency of each DMU can be compared against the frontier and therefore against the most efficient ones. DEA is straight forward to implement and does not require any assumptions on the production function and there is no need for price information. Therefore, DEA is less prone to model misspecification. In fact, DEA creates a "best practice frontier" instead of a "production frontier" [16]. In addition, Sherman and Zhu refer to DEA as a "balanced benchmarking" technique.

As mentioned, DEA builds a piece-wise frontier to calculate the relative efficiencies and inefficiencies of DMUs (in our paper, the US States). The frontier is obtained from the solutions of a series of lps, one lp for each state. Efficient states will appear at the frontier, and the frontier will envelop the inefficient ones. There are two types of DEA models: input-oriented and output oriented. Input-oriented models maintain outputs constant while seeking the maximum possible reduction on the inputs. On the contrary, output-oriented models search for the maximum possible output generation while maintaining inputs at a constant level. It is important to notice that Malmquist productivity index requires output-oriented models. Therefore, in our paper, we present constant returns to scale (CRS) DEA output oriented model results.

Malmquist productivity index

Caves [13], introduced the use of Malmquist indexes to estimate productivity based on distance functions. These indexes are based on the Malmquist quantity index [17]. Fare [18,19], integrated DEA output oriented models with Malmquist productivity indexes. Equation 1 is Malmquist productivity index as presented in fare and Groskopf [18].

$$M_i^{t+1}\left(y_i^t, y_i^{t+1}, x_i^t, x_i^{t+1}\right) = \left[\frac{D_i^t\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} * \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^{t+1}\left(y_i^t, x_i^t\right)}\right]^{1/2} \quad (1)$$

Where x_i^t, y_i^t are the inputs and outputs associated with the i^{th} DMU (e.g. i^{th} State) during the period (e.g., year) *t*. In addition, D^t is the efficiency output distance function associated with x_i^t and y_i^t at time period *t*. Similarly, $D_i^{t+1}(x_i^{t+1}, y_i^{t+1})$ is the output efficiency distance function for time period t+1 in relation to the technology. Notice that the distance function may be less, equal, or greater than one. Also M^{t+1} is the value of the Malmquist index of the most recent data point (x_i^{t+1}, y_i^{t+1}) in relation with the previous production point (x_i^t, y_i^t) The values for $D^t(y^t, x^t)$ $D^t(y^{t+1}, x^{t+1})$ $D^{t+1}(y^t, x^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ are calculated by solving lps (2), (3), (4) and (5) (Equations 2-5).

$$\begin{aligned} & D^t[y_i^t, x_i^t]^{-1} = \max\theta \\ & st \\ & -\theta y_i^t + \lambda Y^t \geq 0 \\ & x_i^t - \lambda X^t \geq 0 \\ & \lambda \geq 0 \end{aligned} \quad (2)$$

Where Θ is a set of variables that measures technical efficiency scores for the i^{th} MU, and λ captures information on the peers of the i^{th} DMU. In general, when M^{t+1} in (1) is greater than 1 is an indication of a positive growth between two consecutive periods. On the other hand, values below 1 indicate a decline in efficiency. In fact, Färe [18], proved that (1) is the geometric mean of two different output-oriented indices (Equations 6 and 7).

$$\begin{aligned} & D^t[y_i^{t+1}, x_i^{t+1}]^{-1} = \max\theta \\ & st \\ & -\theta y_i^{t+1} + \lambda Y^t \geq 0 \\ & x_i^{t+1} - \lambda X^t \geq 0 \\ & \lambda \geq 0 \end{aligned} \quad (3)$$

$$\begin{aligned} & D^{t+1}[y_i^t, x_i^t]^{-1} = \max\theta \\ & st \\ & -\theta y_i^t + \lambda Y^{t+1} \geq 0 \\ & x_i^t - \lambda X^{t+1} \geq 0 \\ & \lambda \geq 0 \end{aligned} \quad (4)$$

$$\begin{aligned} & D^{t+1}[y_i^{t+1}, x_i^{t+1}]^{-1} = \max\theta \\ & st \\ & -\theta y_i^{t+1} + \lambda Y^{t+1} \geq 0 \\ & x_i^{t+1} - \lambda X^{t+1} \geq 0 \\ & \lambda \geq 0 \end{aligned} \quad (5)$$

$$M_i^t = \frac{D_i^t\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} \quad (6)$$

$$M_i^{t+1} = \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^{t+1}\left(y_i^t, x_i^t\right)} \quad (7)$$

Notice that (6) point of reference is period *t*, while (7) point of reference is period *t*+1. Fare [18], showed that productivity can be decomposed in two mutually exclusive components: Technical Efficiency (TE), and Technical Change (TC). Equation 8 shows Malmquist index decomposition; equation 9 is the TC component and equation (10) is the TE component.

$$M_i^{t+1}\left(y_i^t, y_i^{t+1}, x_i^t, x_i^{t+1}\right) = \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)}\left[\frac{D_i^t\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} \times \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^{t+1}\left(y_i^t, x_i^t\right)}\right]^{1/2} \quad (8)$$

$$TE = \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} \quad (9)$$

$$TC = \left[\frac{D_i^t\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^t\left(y_i^t, x_i^t\right)} \times \frac{D_i^{t+1}\left(y_i^{t+1}, x_i^{t+1}\right)}{D_i^{t+1}\left(y_i^t, x_i^t\right)}\right]^{1/2} \quad (10)$$

The decomposition of the Malmquist index in TE and TC implies that DMUs can grow based on innovative production technologies (TC) and/or through a better utilization of inputs (TE). That is, TC is a consequence of new products, technologies, and processes that displace the production frontier. On the other hand, TE indicates whether efficiency is moving toward or away of the best practice frontier between consecutive periods. Values above 1 in TE and TC indicated efficiency increases and values below are a consequence of decrease in efficiencies.

Results

CRS efficiencies and Malmquits Indexes were obtained using data from the Henry J. Kaiser family foundation. Figure 1 is CRS efficiencies for each state This figure shows the different levels of efficiencies over a six-year span (2008-2014). The darker the color of the state, then the more efficient the state is relative to the other states. Complete results are available in Appendix 1.

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The map was built using R packages choroplethr [20,21]. CRS efficiencies and Malmquist Indexes were obtained using data from the Henry J. Kaiser family foundation. Figure 1 displays CRS efficiencies for each state. This figure shows the different levels of efficiencies over a six year span (2008-2014). The darker the shading color of the state, then the more efficient the state is relative to other states. Complete results are available in Appendix 1. The map was constructed using R packages choroplethr Lamstein and Johnson [20], and choroplethr Maps [21]. Since the averages do not reflect improving or deteriorating rates, slope from linear regressions (CRS on time) were obtained for each state. Figure 2 displays these slopes. The slopes are represented as percentages. A negative value indicates a loss of efficiency against frontier states; whereas, a positive value indicates a state is approaching closer to the efficiency frontier. Notice that slopes for the most efficient states have values of zero. This is because these states have CRS values of 1.00 for each analyzed year.

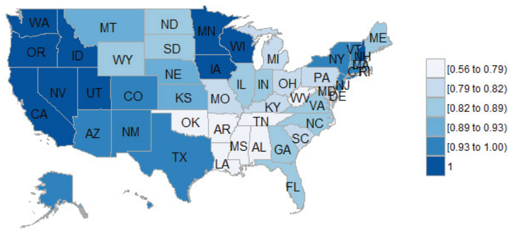

Figure 1: Average constant returns to scale efficiencies (2008-2014).

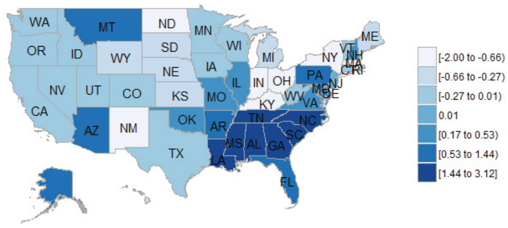

Figure 2: CRS slopes (2008-2014).

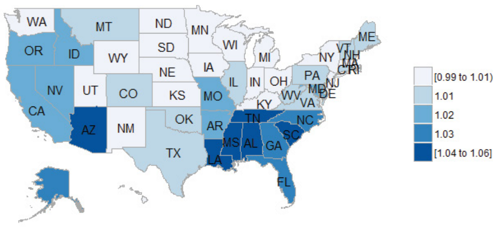

Figure 3: Average Malmquist index (2008-2014).

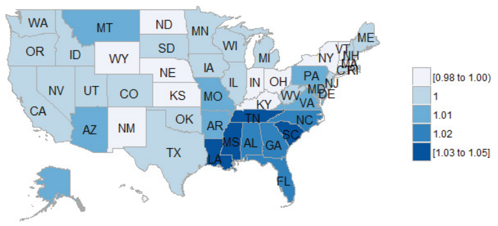

Figure 4: Average Malmquist efficiency index (2008-2014).

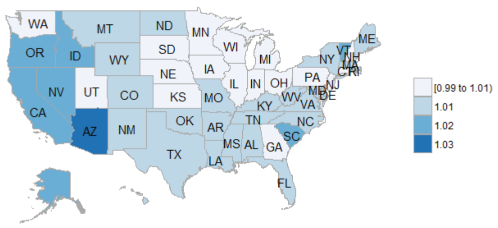

Figure 5: Average Malmquist technical index (2008-2014).

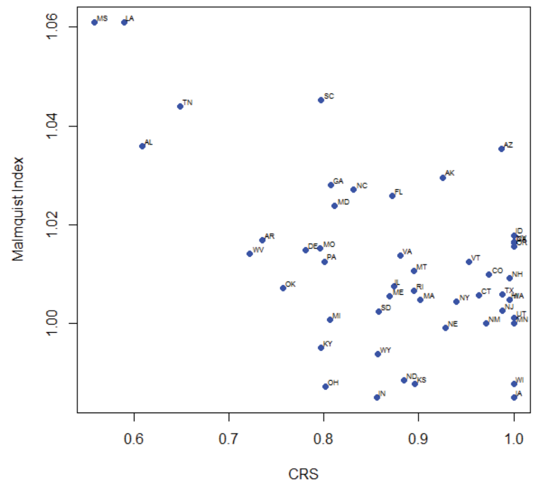

Figure 6: CRS versus Malmquist index average.

The Malmquist productivity Index measures how states change from one year to the next year. Figure 3 shows the Malmquist productivity index average for the 50 states and Appendix 2 contains additional details regarding the data results. As mentioned in the methods section, Malmquist productivity index can be decomposed into two components: Malmquist efficiency index and Malquist technology index. Malquist efficiency index results are summarized in Figure 4 and detailed results are shown in Appendix 3.

Malmquist efficiency index measures efficiency improvements based on better utilization of resources. On the other hand, Malmquist technology index measures improvements due to technological changes. Figures 5-8 summarizes Malmquist technology index and detailed results are presented in Appendix 4. This plot shows the 50 states compared with each other.

Discussion

There have been a few DEA studies to assess the different aspects of the medical field such as hospital efficiency [22-25], public polices efficiency [26-29], or health facilities efficiency [30-32]. Our study demonstrates that there are varying levels of efficiency in the utilization of health resources (i.e., number of physicians, number of hospital beds and public health expenditures) among the 50 US states. We used three input variables-the number of physicians per 100,000 residents per state, the number of hospital beds per 1000 inhabitants per state and the public health funding per capita per state and one output variable-disability adjusted life years to reflect burden of disease.

Figure 1 shows a clustering effect of efficiencies with two distinct regions appearing most efficient vis-à-vis the other states. It appears that the Western US (i.e., Washington, Oregon, Idaho, California, Nevada and Utah) and the northern most Midwest regions (Minnesota, Iowa and Wisconsin) are the most efficient relative to the other states. The least efficient are clustered in the south Midwestern region (i.e.,

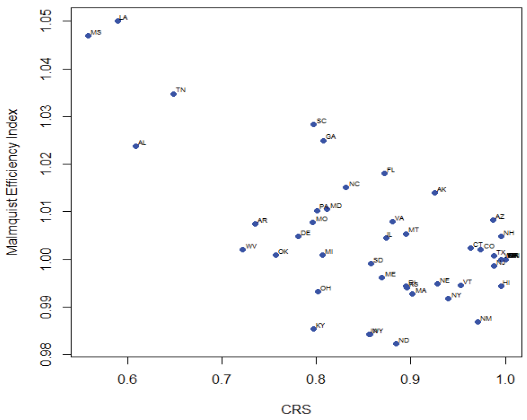

Figure 7: CRS Average compared to the Malmquist efficiency index average.

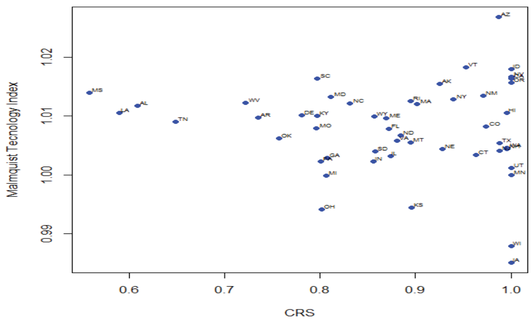

Figure 8: CRS to the Malmquist technology index.

Oklahoma, Arkansas, Tennessee, Louisiana, Mississippi, West Virginia and Alabama**.** Figure 2 demonstrates that the south eastern states which have relatively low CRS efficiencies (i.e., Louisiana, Mississippi, Alabama, Georgia, North and South Carolina, and Tennessee) have improved their health resource utilization efficiencies over the duration of this study (2008-2014).

The Malmquist index average (Figure 3) shows efficiency improvements by comparing each state vis-à-vis the other states. This figure suggests that most states have been improving in their efficiencies over the six year span examined in this paper. This may reflect a concerted effort by state legislatures to improve health efficiencies with the advent of increased financial constraints after the significant recession of 2007-2009. The states showing the most improvement include the previously least efficient southeastern states (i.e., Louisiana, Mississippi, Alabama, Georgia, North and South Carolina, and Tennessee). The first scatter plot (Figure 6) compares CRS efficiences with the the Malmquist Index average overall. The other scatter plots (Figures 7 and 8) compare the CRS efficiency with each component of the Malmquist index average (i.e., the efficiency index and the technology index). The first scatter plot illustrated in Figure 6 shows that states with low CRS efficiencies tend to show larger Malmquist index averages. This indicates that these southeastern states are "catching up" or improving relative to the other states, but still have a large gap in efficiency utilization. Figure 7 shows that states with lower CRS efficiencies tend to have higher Malmquist Efficiency Indexes. Thus, these states appear to be improving in the fashion and manner that they manage their limited resources. Consequently, the amount of waste in these southeastern states have been reduced through the years.

Figure 8 compares the CRS average to the Malmquist technology index. However, it does not show a clear trend. The Western states (i.e. Washington, Oregon, Idaho, California, Nevada and Utah) with high CRS efficiency values also have higher technology indexes. In contrast, the north-Midwestern states with high CRS efficiency values have lower Malmquist technology indexes (e.g. Minnesota, Wisconsin and Iowa). This paradox appears to show that these North-Midwestern states are efficient with their use of health resources, but their efficiency is not due to technological improvements as in the western states. Rather it appears to be a result of improved management of limited health resources.

This study has several limitations. First, the advent of the patient protection and affordable care Act which was ratified in 2010 and initiated in 2013. This could affect the data midway within the study because of altering state resource utilizations. For instance, some states chose to significantly expand Medicaid with federal funding assistance while others did not expand their state programs. Second, the data may be distorted by the effects and ramifications of the great recession of 2007-2009 which may have affected each state differently. Third, there are inherent methodological difficulties in assessing the efficiency of health systems such as the health status of citizens which influences the productivity level. Lastly, the selection of input and output variables affects the results. Consequently, the research should be extended by incorporating and altering these variables to examine different efficiency outcomes.

References

1. Mokdad AH, Marks JS, Stroup DF, Gerberding JL (2004) Actual causes of death in the United States, 2000 JAMA 291: 1238-1245.
2. Field M, Gold MR (1998) Summarizing population health. National Academy Press, Washington DC, USA.
3. McKenna MT, Michaud CM, Murray CJL (2005) Assessing the Burden of Disease in the United States Using Disability-Adjusted Life Years. Am J Prev Med 28(5): 415-423.
4. U.S. Department of Health and Human Services. Tracking healthy people 2010. U.S. Government Printing Office, Washington, DC, USA.
5. Murray CJL, Salomon JA, Mathers CD (2002) Summary Measures of population health. World Health Organization, Geneva.
6. Putzer G, Jaramillo J (2015) Premature Mortality Costs Associated with Lifestyle Factors among US Citizens. Review Pub Administration Manag 3:177
7. World Bank (1993) World development report 1993: investing in health. New York: Oxford University Press, USA.
8. Murray CJ, Lopez A (1996) The global burden of disease: a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 and projected to 2020. Cambridge: Harvard University Press, USA.
9. World Health Organization (2001) World health report 2001: Mental health, new understanding, new hope. Geneva: World Health Organization, USA.
10. Molla M, Madans J, Wagener D (2003) Summary measures of population health: report on the findings on methodological and data issues, Hyattsville, MD: National Center for Health Statistics, USA.
11. Asandului L, Roman M, Fatulescu P (2014) The efficiency of healthcare systems in Europe: A data envelope analysis approach. Pro Eco Fin 10: 261-268.
12. Roh CY, Park C, Moon MJ (2011) Economic performances of US non-profit hospitals using the Malmquist productivity change index. J Mang and mang res 8: 1-16.
13. Caves D, Christensen L, Diewert W (1982) The economic theory of numbers and the measurement of input, output, and productivity. Econometrica 50(6): 1393-1414.
14. Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 1: 429-444.
15. Farrell MJ (1957) The measurement of productive efficiency. JSTOR 120: 253-281.

16. Cook WD, Tone K, Zhu J (2014) Data envelopment analysis: Prior to choosing a model, Omega 44: 1-4.

17. Malmquist S (1953) Index numbers and indifference surfaces. Trabajos de Estadística 4: 209-242.

18. Fare R, Grosskopf S, Lovell CAK, Pasurka C (1989) Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. Rew Econ and Stat 71: 90-98.

19. Fare R, Grosskopf S, Lovell CAK (1994) Production frontiers. Cambridge University Press.

20. Lamstein AR. Package choroplethr Maps version 1.0 Trulia Inc.

21. Lamstein A, Johnson BR. Package choroplethr version 3.5.2. Trulia Inc.

22. Tambour M, Rehnberg C (1997) Internal markets and performance in Swedish health care. Working paper in economics and finance. 161, Stockholm School of Economics.

23. Zhu J (2002) Quantitative models of performance evaluation and benchmarking: Data envelope analysis with spreadsheets and DEA excel solver, Kluwer academic publishers, Boston.

24. Nedelea IC, Fannin JM, Barnes JN (2010) Analyzing differences in rural hospital efficiency: A data envelope analysis approach. 2010 annual meeting 2010, Denver, Colorado 61391. Agricultural and Applied Economics Association.

25. Mecineanu A, Soltan V (2012) Eficienta spitalelor publice din republica moldova. Monitorul Sanatatii. Chisinau 2012.

26. Coppola M, Ozcan Y, Bogacki R (2003) Evaluation of performance of dental providers on posterior restorations: does experience matter? A data envelope analysis (DEA) approach. J Med sys 27(5): 447-458.

27. Miller JL, Adam EE (1996) Slack and performance in health care delivery. Int J Qty Rby Mag 13(8): 63-74.

28. Sherman H (1984) Hospital efficiency measurement and evaluation: empirical test of a new technique. Medical Care Med c 22(10): 922-938.

29. Rosko M (1990) Measuring technical efficiency in health care organizations. J Med Sys (14)5: 307-322.

30. Hollingsworth B (2008) The measurement of efficiency and productivity of health care delivery. Health Economics, Hlth econ 17(10): 1107-1128.

31. Ozcan YA (2008) Health care benchmarking and performance evaluation: An assessment using data envelope analysis. Springer; Norwell, MA.

32. Rosko MFG, Valdmanis V (2006) Analysis of uncompensated hospital care using a DEA model of output congestion. Health Mang Sci 9: 181-188.