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Efficiency in general medical practice in the Czech Republic

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Abstract

This bachelor thesis analyses technical efficiency of general practitioners in the Czech Republic. It exploits unique dataset that comprises information about health care activities of 107 general practitioners that operate in 79 different municipalities over the period 2015-2017. First, Principal Component Analysis was utilized to deal with high dimensionality of medical outputs. Second, two stochastic frontier regression models were employed, one of which accounts for heterogeneity of the sample by including efficiency effects variables. Even though both models estimate mean technical efficiency to be approximately 83 %, efficiency ranking of individual general practitioners differs across models. Included efficiency effects have statistically significant impact on technical efficiency. In particular, general practitioners situated in rural municipalities are less efficient, higher competition in a municipality discourages efficiency and general practitioners providing health care to adults are more efficient.

Abstrakt

Tato bakalářská práce analyzuje technickou efektivitu českých praktických lékařů. Využívá při tom unikátní dataset, který obsahuje informace o zdravotnických aktivitách 107 praktických lékařů, kteří působí v 79 různých obcích v letech 2015-2017. Nejprve je použita analýza hlavních component, která slouží ke snížení dimenzí lékařských výkonů. Poté jsou použity dvě stochastické hraniční regrese, kde jedna z nich vysvětluje heterogenitu zkoumaného vzorku přidáním proměnných, které ovlivňují efektivitu (efekty efektivity). Přestože oba dva modely odhadují 83% průměrnou technickou efektivitu zkoumaného vzorku, pořadí, založené na velikosti efektivity jednotlivých praktických lékařů, se liší mezi zkoumanými modely. Přidané efekty efektivity mají statisticky signifikantní vliv na technickou efektivitu. Konkrétně, praktičtí lékaři působící ve vesnicích jsou méně efektivní, zvýšená konkurence v obci lékaře má negativní dopad na jeho efektivitu a praktičtí lékaři poskytující péči dospělým jsou více efektivní.

Keywords

General Practitioners, Health Care,Technical Efficiency, Stochastic Frontier Analysis, Czech Republic

Klíčová slova

Praktičtí lékaři, Zdravotní péče, Technická efektivita, Analýza stochastické hranice, Česká republika

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, 11 May 2018

Signature

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Acronyms

AE Allocative Efficiency

CO Capitation Outputs

DEA Data Envelopment Analysis

DMU Decision Making Unit

EE Economic Efficiency

GP General Practitioner

HC Health Care

MLE Maximum Likelihood Estimation

NCO Non-Capitation Outputs

PC Principal Components

PCA Principal Components Analysis

SFA Stochastic Frontier Analysis

TE Technical Efficiency

Contents

Introduction

Health systems are currently faced with challenges, such as multimorbidity, chronic diseases, or continuously rising expenditures, that arise from population ageing, changing epidemiological patterns and technological advances. In the Czech Republic, 7.4 % of GDP is spent on health care (HC) which represents 18.9 % of total government spending; the second highest proportion in the EU. Yet, the efficiency of the entire system is one of the worst in the EU (Medeiros et al., 2015).

General practitioners (GPs) serve as a cornerstone in many health systems (Starfield, 2001). They represent the first point of contact with professional HC services in ambulatory setting where the vast majority of health issues are dealt with (Van Lerberghe, 2008). In particular, they make the first diagnosis, choose an initial therapy and if needed, refer their patients to specialists and hospitals where subsequent measures are carried out. This role is termed as gatekeeping role (Scott, 2000).

In the **Czech Republic**, the range of services provided by GPs is regulated by the state, the regions and the health insurance funds. Gatekeeping role of GPs is considerably weakened as patients may access HC directly from a specialist, and they frequently do so (Alexa et al., 2015). GPs bear virtually no financial risk regarding treatment cost. They are mostly compensated by capitation payments[1] and for selected procedures, usually associated with preventative examinations, fee-for-service is employed. In primary care, GPs consume the largest share of expenditure (Alexa et al., 2015). Furthermore, they are interconnected with the entire health system and their decisions influence even larger proportion of total spending on HC (Eisenberg, 1985). Hence, performance of GPs is critical topic for priority setting by policy makers.

This thesis attempts to examine performance of a sample of GPs that operate in the Czech Republic. Stochastic Frontier Analysis (SFA) is employed to analyse technical efficiency (TE) of the GPs, generally referred

[1] Periodical lump-sum payment adjusted for age of a patient that a GP receives payment for

to as decision making units (DMUs), over the period 2015-2017. To the best of our knowledge, there has not been any literature on assessing performance of GPs in the Czech Republic, and thus it may not only provide valuable insight for policy makers but also encourage further research in this area.

This bachelor thesis is organized as follows. Chapter 1 summarizes available literature on measuring efficiency in HC and emphasizes the contribution of the thesis. Chapter 2 provides theoretical framework of production in HC and stresses the complexity of both the production process and the corresponding assessment of its performance. Chapter 3 describes TE and methodology that is employed to measure it. Chapter 4 describes dataset and variables used in the SFA. Chapter 5 is devoted to Principal Component Analysis that is used to transform excessive number of outputs provided by GPs into 5 Principal Components that enter the analysis. In Chapter 6, empirical results of the SFA models are interpreted, compared and their relevance is discussed. Finally, there is a conclusion of the whole thesis.

1 Literature Review

Efficiency in HC has been examined for a relatively long period of time. There is a large supply of literature regarding both methodology and applications of efficiency analysis. Yet, there are some areas in HC whose performance has not been adequately assessed.

This section is divided into 3 parts - Measuring Efficiency in Health Care, Measuring Efficiency in the Czech Republic and Measuring Efficiency in Primary Care. Examination of these topics is vital to thoroughly understand and conduct efficiency analysis of general GPs in the Czech Republic.

1.1 Measuring Efficiency in Health Care

There is literature regarding both metadata and guidelines for measuring efficiency in HC. The majority of academic work focuses on evaluating efficiency of hospitals' performance, yet most of the theory is applicable to GPs as well.

There is a mismatch between high supply of efficiency analyses by academics and low demand by policy makers. (Hollingsworth, 2008). Due to poor data availability, efficiency analysis is limited and does not provide the whole picture about performance of DMUs in HC (Jacobs et al., 2006). Hence, policy makers are rather hesitant when making any conclusions and potentially policy changes based on these analyses (Smith, 2009). Hussey et al. (2009) found out in their systematic review of existing efficiency measures, that vendor-developed measures, stated in "grey" literature[2], are more commonly used for decision making in HC than measures developed by academics. Recently, there have been attempts to set guidelines for both efficiency measurement and interpretation of results which contribute to consistency and easier application in a health system, e.g. in Mutter et al. (2011) or in Cylus et al. (2016).

[2]Literature that is not published. In this case, gathering information through interviewing private organizations that developed their own efficiency measures

Generally, there are two approaches to measurement of efficiency - parametric and non-parametric methods. Stochastic frontier analysis (SFA), a parametric method, and Data envelopment analysis (DEA), a non-parametric method, are employed most frequently (Hussey et al., 2009). DEA can take advantage of more detailed data, i.e. multiple inputs and outputs, and analysts usually opt for this approach as they do not need to make strong assumptions (required by SFA) for which there are no economic explanations (Jacobs et al., 2006). Nevertheless, the application of SFA in HC has been rising recently. Perhaps due to its increased potential in panel data analysis and its inclusion in econometrics software packages that are widely used (Hollingsworth, 2008). Both SFA and DEA are applicable to both cross-sectional and panel data (Coelli et al., 2005).

Probably the most difficult challenge presented in the literature is associated with model specification. In particular, there is an ongoing discussion about proper use of environmental and quality variables in the models. Specification of environmental variables is relatively straightforward. Generally, significant environmental variables consist of facility type, size of DMU, rural/urban environment, proportion of older (65+ years) population, e.g. in Pai et al. (2000) or in Cordero-Ferrera et al. (2011). On the other hand, choice of quality variables is rather exacting for analysts as it is hard to define and quantify quality of HC provision. Several different proxy variables were used, e.g. affirmative answers to questions indicating quality of service in primary care (Puig-Junoy and Ortún, 2004) or experience of GPs measured as number of days at work during previous 15 years (Ferrera et al., 2014). Some argue that both environmental and quality variables have impact on the values of efficiency, and thus each efficiency analysis should account for them (Rosko and Mutter, 2008; Kontodimopoulos et al., 2007). If they are not included, one is left with analysis of cost (rather than efficiency) of HC of DMUs that are examined (Hussey et al., 2009). On the other hand, in some studies, environmental variables were not statistically significant (for $p < 0.05$) (Vitaliano and Toren, 1996; Zuckerman et al., 1994).

Concerning SFA, specification of functional form has to be determined. Usually either Translog or Cobb-Douglas function is employed. In addition, crucial choice has to be made about the distribution of efficiency in the error term. Conventionally, exponential, half-normal or exponential distribution are employed (Rosko and Mutter, 2008). In this case, there is not any consensus about which distribution is right. To illustrate,Murillo-Zamorano and Petraglia (2011) selected half-normal, Laberge et al. (2016) exponential and Puig-Junoy and Ortún (2004) truncated distribution of efficiency.

Finally, Medeiros et al. (2015) and Mossialos (2017) provide the most recent insight into efficiency measurement of the entire health systems in the EU countries. They analyse methodologies, choice of different variables and results of efficiency studies to benchmark performance of the EU members. However, Greene (2004) points out, that comparison of efficiencies of health systems at macro level does not adequately account for heterogeneity which might be confused with inefficiency[3].

1.2 Measuring Efficiency in the Czech Republic

The Czech Republic is among EU countries with the lowest efficiency of its health system[4] (Medeiros et al., 2015). Generally, there is a lack of academic work regarding measuring HC efficiency in Czechia, and thus further analysis in this area should be conducted.

Chronologically, Dlouhý et al. (2007) pioneered efficiency analysis in the Czech health system, specifically in hospitals. They analysed 22 hospitals using DEA method employing both BCC (varialbe-returns-to-scale) and CCR (constant-returns-to-scale). By definition, each method produced different results regarding both rank of hospitals and values of individual efficiencies. Furthermore, due to low data availability they could not control for variables, such as quality of HC or environmental constraints. Similarly,

[3] The sample included 191 WHO countries associated with wide variation in cultural and economic characteristics, i.e. with higher level of heterogeneity than among EU countries

[4] Relative efficiency was estimated based on models with different combinations of outputs (e.g. life expectancy, healthy life expectancy and amenable mortality rates) and inputs (HC expenditure, physical inputs and environmental variables)

Novosádová and Dlouhý (2007) carried out study to examine efficiency of 119 Czech hospitals employing the same approach as Dlouhý et al. (2007). They report similar limitations of the study regarding data.

Votápková et al. (2013) employed SFA method using panel data of Czech hospitals. They managed to account for both environmental constraints and quality that affect efficiency of hospitals. For instance, they include size of hospital, for profit/not-for-profit status, population size, number of hospitals in the same region. They conclude that such variables have expected sign and are significant. Furthermore, they report mean efficiency of Czech hospitals to be 87 %. Šťastná and Votápková (2014) apply quite complex order-m approach which is beyond the scope of this text. They analysed efficiency of 81 Czech general hospitals and found that the efficiency of Czech hospitals worsened in periods 2009-2010 due to additional increase in revenues by user charges introduced in 2008. Last, Votápková (2011) employs both SFA and DEA methods and compares their results. She concludes that both methodologies produce qualitatively similar results across all the methods used for only small hospitals.

There is not any literature analysing efficiency of GPs in the Czech Republic. They are very important in Czech health system as they consume relatively large share of total expenditure on HC (5.8 %), in fact the largest share of primary care (Alexa et al., 2015). Hence, presumably, there is a need for such analysis

1.3 Measuring Efficiency in Primary Care

In the published literature, there is a lack of analysis regarding efficiency of GPs[5]. Instead, measuring efficiency in primary care was examined; which, among other DMUs, includes GPs[6]. Until 2008, there had been published 317 papers analysing performance of DMUs in HC, yet only 19 of them concentrate on primary care (Hollingsworth, 2008).

[5] To our knowledge, there are only four studies analyzing efficiency solely of GPs (Szczepura et al., 1993; Thornton, 1998; Staat, 2003; Pelone et al., 2012)

[6] Most of the studies incorporate samples that are more heterogenous in terms of specialization of DMUs

The majority of the analyses use non-parametric methods, specifically data envelopment analysis (DEA) is employed. The classical DEA model is used for cross-sectional data, e.g. in Andes et al. (2002), and the Malmquist index is used for panel or longitudinal data, e.g. in Giuffrida (1999). Even though the use of the SFA method is on rise in HC (Hollingsworth, 2012), available academic work concerning the SFA of efficiency in primary care is rather scarce.

In the SFA, both production and cost function estimation can be observed in primary care efficiency analyses. Former is implemented by Puig-Junoy and Ortún (2004); latter byMurillo-Zamorano and Petraglia (2011) and Laberge et al. (2016). Regarding data, number of observations differs quite substantially in each study, yet the majority of them falls into the range between 80 and 200 observations. Almost all studies are cross-sectional in nature (Thornton, 1998; Deidda et al., 2014) rather than longitudinal (Staat, 2003). This clearly indicates room for improvement, as panel data bring several benefits (for more on this see Chapter 3). In total, there are only three studies that incorporate panel data; all of them use the DEA (Malmquist) approach. For instance, Szczepura et al. (1993) took advantage of panel data to examine impact of certain policy (GP contract introduced in 1991 in the UK) and found its positive effect on efficiency of GPs.

This thesis will contribute to efficiency analysis in HC as it will both analyse efficiency of GPs as a homogenous sample and employ longitudinal data which are scarce in analysis of HC performance.

2 Health Care Production

Production process in HC differs quite substantially from the one of a typical production-line type unit. Specifically, production-line type unit consumes inputs and produces outputs that are both clearly identified. Whereas, HC produces outputs that are tailor-made to the concrete needs of a patient, which makes the production more complex (Harris, 1977), and thus assessing the efficiency of the entire process is considerably challenging. Figure 2.1 serves as an illustration for HC production.

Entity under scrutiny can take different forms in HC. For instance, it relates to a single treatment at the finest micro level; to individuals or groups of practitioners, teams, hospitals, or other organization at the meso level; and to the entire system at the macro level (Cylus et al., 2016). Entities at meso and macro level are referred to as decision making units (DMUs) in efficiency analysis. The entire health system is **interconnected**, therefore it is necessary to take into account the role and position of the entity in such a system.

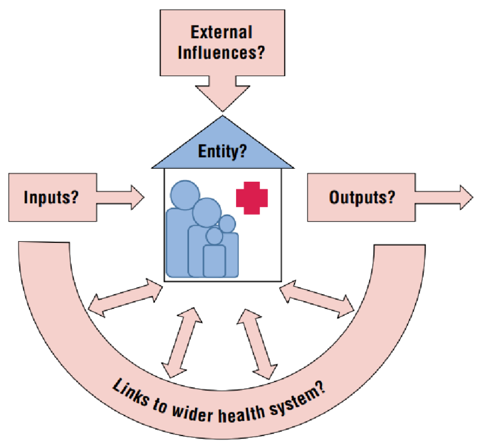
While in a majority of competitive industries traded product of a DMU is the **output**, the output of HC is health outcome. It is associated with the impact of a particular medical intervention on health status[7] of a patient (Smith, 2009). Health is a complex concept which is not only hard to define but also difficult to attribute some value to it. Even though, there are some measurements evaluating before/after measures of HC treatment, such as EQ5D or SF36 (EuroQol, 1990; Ware Jr and Sherbourne, 1992), HC DMUs do not keep track of such measures in most of the cases. Hence, usually HC activities are employed instead in efficiency analyses as proxies for helath outcomes.

In HC, **inputs** are easier to identify. They can be measured more precisely than outputs, yet their measurement imposes some difficulties in efficiency analysis as well. Main challenge is associated with the decision about the level of disaggregation of inputs (Jacobs et al., 2006).

[7] State of patient's health at a particular time

In a long-run perspective, only low level of disaggregation is necessary; usually up to the point that single measure represented by total costs is sufficient. However, analysts have to rely on the assumption that a DMU utilizes inputs efficiently (Mossialos, 2017). In a short-run perspective, this assumption almost certainly does not hold as the DMU under scrutiny does not have full control over the input mix. For instance, the DMU cannot immediately adjust its mix of inputs to sudden changes of market prices . It is therefore necessary to disaggregate inputs in order to account for different mixes that the DMU employs over time. Typically, such inputs are labour and capital.

Figure 2.1: Health Care Production Process



Source: Mossialos (2017)

Production process of the DMU can be affected by **external factors** that are beyond control of the DMU. These external factors relate to the health characteristics of the local population, local transport, geography and economic conditions, and the activities of other agencies both inside and outside the health sector (Smith, 2009). There are different ways to account for such factors in the efficiency analysis. One can restrict comparison only to entities operating within a similarly constrained environment (Mossialos, 2017); these constraints can be modeled explicitly by using regression analysis (Jacobs et al., 2006); or risk adjustment can be undertaken to adjust outcomes achieved to reflect external constraints (Iezzoni, 1997).

3 Methodology

3.1 Efficiency

Farrell (1957) pioneered productive efficiency measurement. In his work, he describes what is meant by technical efficiency through microeconomic theory and provides its measure that takes into account all inputs of a DMU (firm, industry, etc.). In particular, his method estimates production function (frontier) where inefficiency is demonstrated as departure from such frontier. Charnes et al. (1978) contributed to this theory by introducing allocative efficiency, which takes into account prices of input and the optimal mix of inputs used in production. Currently, both terms are used and they together represent economic efficiency.

Unit under scrutiny is a DMU that performs certain production process in which inputs are transformed into outputs. It is treated as a "black box" which consumes various costly inputs (labour, capital, etc.) and produces valued outputs (specific to characteristics of a firm). Efficiency analysts aim to measure how well (efficiently) this process is carried out.

Economic efficiency can be defined by following formula:

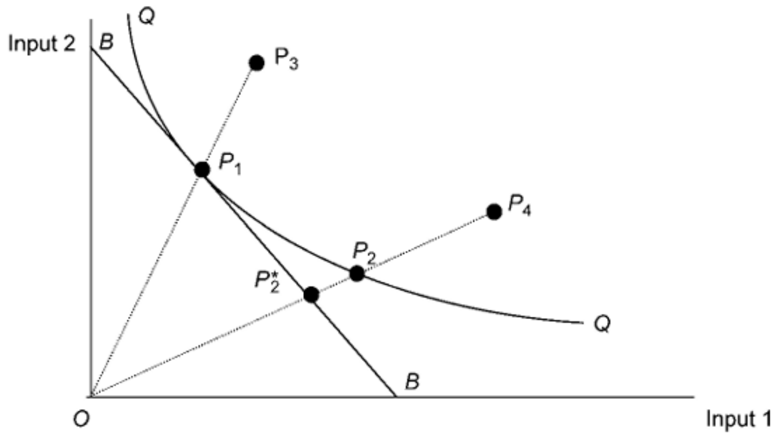
$$e_0 = \frac{\sum_{s=1}^{S} U_s Y_{s0}}{\sum_{m=1}^{M} V_m X_{m0}} \tag{3.1}$$

Where e_0 is efficiency of DMU 0, Y_{s0} is the amount of the sth output produced by organisation 0, U_s is the weight given to sth output, X_{m0} is the amount if the mth input consumed by organisation 0 and V_m is the weight given to mth input (usually reflected by market price).

Technically efficient DMU produces maximum possible amount of outputs with given amount of inputs (output augmentation). Analogically, TE holds if a DMU employs minimum possible amount of inputs to produce desired level of output (input reduction). Assessment of TE does not require any information about input/output prices. For illustration, Figure 3.1

is used. There are two inputs being used to produce given level of output. The isoquant (QQ) represents a minimum attainable mix of inputs that a secure required level of output. TE of a DMU is represented by the distance from the estimated isoquant.

Figure 3.1: Economic Efficiency



Allocative efficiency is a concept that indicates to what extent a DMU either purchases the right mix of inputs or produces the right mix of outputs. Assessment of AE is therefore dependent upon knowledge of prices of both outputs and inputs. In Figure 3.1, the slope of BB is determined by market prices of both input 1 (V_1) and input 2 (V_2) and its value equals: -V_1/V_2. From microeconomic theory, a cost-minimising point is on the isoquant where the slope of QQ equals the slope of BB (i.e. -V_1/V_2). DMU P_1 is allocativelly efficient with respect to input prices as it employs the right mix of inputs. On the other hand, DMU P_2 exhibits some allocative inefficiency. For its mix of inputs, it would have to operate outside the isoquant QQ (not attainable), in fact at the point P_2^*, to be cost-minimizing.

Finally, **economic efficiency** can be demonstrated by combining explanations of both TE and AE. DMU P_1 exhibits 100% EE. DMU P_3 is allocatively efficient as it consumes the right mix of inputs. However, it lies inside the isoquant and is therefore technically inefficient. EE equals the ratio OP_1 / OP_3. DMU P_4 is both technically and allocatively inefficient. AE is represented by ratio OP_2^* / OP_2 and TE by OP_2 / OP_4. Such DMU thus not only incorporates wrong mix of inputs (AE) but also employs excessive amount of inputs to produce produce given level of output (TE). The overall level of inefficiency of DMU P_4 equals OP_2^* / OP_4

3.2 Estimating Efficiency

General approach of the efficiency analysis includes measurement of inputs and outputs. Then certain relationship is observed between them, which is represented by estimated frontier. The inefficiency of a single DMU is then defined as difference, or at least some part of such difference, between estimated frontier (cost function/production function) and the observation.

There are several techniques for estimating production/cost frontier; hence, they are called frontier methods. Frontier methods can be divided into two extensive categories - parametric methods and non-parametric methods (Coelli et al., 2005). While former employs econometric techniques to estimate parameters of a frontier, latter exploits observed data to construct frontier without any assumptions about either functional form or distributions efficiency. The most widely used parametric method is Stochastic Frontier Analysis (SFA); Data Envelopment Analysis (DEA) is the most common non-parametric method (Hollingsworth, 2008).

Generally, the choice of technique should be made based on the purpose of the study and type of data (Hjalmarsson et al., 1996). Efficiency analysis in the thesis employs **Stochastic Frontier Analysis** since both econometric approach is preferred and available panel data are more suitable for the SFA.

3.3 Stochastic Frontier Analysis (SFA)

When the SFA is employed in efficiency estimation, only technical efficiency is taken into account (Coelli et al., 2005). Henceforth, efficiency, when mentioned in the thesis, relates solely to technical efficiency.

Independently of each other Aigner et al. (1977) and Meeusen and van Den Broeck (1977) introduced the SFA, even though the name was used only by Aigner et al. (1977). Their models were initially designed for cross-sectional data. Battese and Coelli (1988) extended the SFA approach to panel data. Further, there has been an ongoing discussion about time-(in)variancy, determinants and distribution of efficiency. Accordingly, many alternatives of the SFA have been developed[8].

The inital cross-sectional model of the SFA proposed by Aigner et al. (1977) has the following form:

$$q_i = f(\boldsymbol{x_i}; \boldsymbol{\beta}) + v_i - u_i; \quad i = 1, ..., N; \tag{3.2}$$

where q_i is the production of the i-th DMU, $\boldsymbol{x_i}$ is a K $\times$ 1 vector of input quantities of the i-th DMU, $\boldsymbol{\beta}$ is a vector of unknown parameters, N represents the number of DMUs in the sample.

The error term is decomposed into two parts. Component v_i represents the symetric disturbance: v_i is assumed to be independently and identically distributed (iid) as $N(0, \sigma_v^2)$. The second component u_i represents inefficiency of the i-th DMU. It is assumed to be distributed independently of v_i and to satisfy $u_i \geq 0$; the distribution of u_i is derived from $N(0, \sigma_u^2)$ truncated above at zero. Other one-sided distributions of u_i are possible, e.g. exponential or gamma distribution (Greene, 1991).

Equation 3.2 takes into account output as dependent variable and estimates **production function**, and thus it refers to output augmentation perspective. In HC, DMUs cannot influence the amount of output as much as the amount of inputs involved in the production. Hence, when performing efficiency analysis in the thesis, the input reduction point of view is taken into account. Consequently, models in the thesis estimate **cost function**. Since these approaches are analogous, methodology of Aigner et al. (1977) is applicable to estimation of cost function as well and has the following form:

$$C_i = f(\boldsymbol{Y_i}; \boldsymbol{\beta}) + v_i + u_i; \quad i = 1, ..., N; \tag{3.3}$$

where C_i are total costs of the i-th DMU, $\boldsymbol{Y_i}$ is a K $\times$ 1 vector of output

[8] e.g. by Battese and Coelli (1995), Kumbhakar and Lovell (2003), orGreene (2005)

quantities of the i-th DMU. Components of the error term possess the same characteristics as error componens in Equation 3.2. The change of sign in the error term is important to reflect economic intuition behind the model. Assuming random noise to be zero, negative departure from the cost function does not make any sense as cost function represents minimum costs needed to achieve certain level of output.

In terms of $f(\boldsymbol{Y_i}; \boldsymbol{\beta})$, Cobb-Douglas and Translog (Christensen et al., 1973) functional forms are the most often used functional forms in the SFA (Coelli et al., 2005).

Cobb-Douglas has the following form:

$$\ln C = \beta_0 + \sum_{j=1}^{K} \beta_j \ln Y_j \tag{3.4}$$

Translog has the following form:

$$\ln C = \beta_0 + \sum_{j=1}^{K} \beta_j \ln Y_j + \frac{1}{2} \sum_{j=1}^{K} \sum_{q=1}^{K} \beta_{jq} \ln Y_j \ln Y_p \tag{3.5}$$

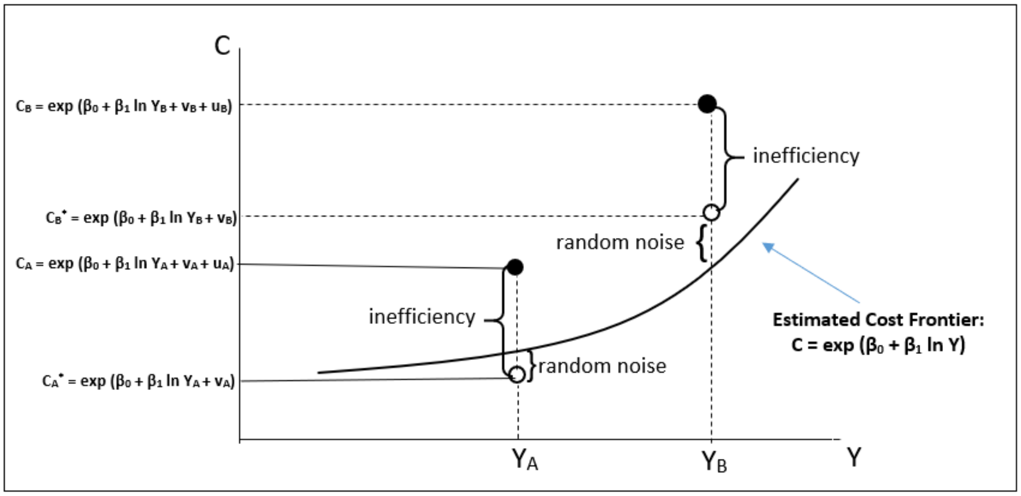
Essentially, Translog functional form is extend Cobb-Douglas by including squares (for $j = q$) and cross product of output variables (for $j \neq q$). This thesis takes in to cosideration both of theses functional forms.

Figure 3.2 illustrates Stochastic Cost Frontier employing Cobb-Douglas functional form[9]. For simplification, example of one output is used and two firms (A and B) are observed.

Firm A produces Y_A amount of output and consumes C_A amount of total costs. Accordingly, firm B produces Y_B and consumes C_B. These scenarios are indicated as black points ($\bullet$) on the graph. If firms were 100% efficient, i.e. both u_A and u_B were zero, they would be situated on white points ($\circ$). Yet, they would still not operate on the frontier, as can be seen in the Figure 3.2, because part of the deviation from the frontier is attributed to the random noise effect. This is one of the main differences and perhaps advantage compared to the DEA method which attributes deviation from the cost frontier solely to the inefficiency.

[9] Cobb-Douglas is transformed by taking exponential of Equation 3.4

Figure 3.2: The Stochastic Production Frontier



Since the SFA used in the thesis exploits **panel data**, extended model of Aigner et al. (1977) is employed. More efficient estimators of both unkonown parameters and inefficiency are generally expected as panel data sets usually contain more observations than cross-sectional data sets (Coelli et al., 2005). In addition, panel data, under certain circumstances, allow relaxation of some assumptions that must hold for cross-sectional data sets[10].

Extended model takes the following form:

$$C_{it} = f(\boldsymbol{Y_{it}}; \boldsymbol{\beta}) + v_{it} + u_{it}; \quad i = 1, ..., N; \quad t = 1, ..., T; \quad u_{it} \geq 0 \qquad (3.6)$$

where C_{it} are total costs of the i-th DMU at time t, $\boldsymbol{Y_{it}}$ is a K $\times$ 1 vector of output quantities of the i-th DMU at time t, $\boldsymbol{\beta}$ is an vector of unknown parameters, N represents number of DMUs in the sample and T time periods for which observations are available for at least one of the N DMUs involved. The SFA thus allows analyze unbalanced panel data.

Key assumption about time-(in)variancy of efficiency has to be made in panel data analysis. Time-invarint efficiency varies across DMUs but not across time. Generally, time-varying efficiency is employed for longer panels of data (Coelli et al., 2005). Since the panel data exploited in the thesis

[10]For fixed-effects estimator, assumptions about distribution of efficiency can be relaxed due to multiple observations of a single DMU. Furthermore, correlation between explanatory variables and efficiency term can be non-zero (again, only for fixed-effects estimator)

are sufficiently long (3 years) **time-varying** efficiency is assumed in the SFA.

As was foreshadowed in Chapter 1, there is not a consensus among analysts whether it is appropriate to account for heterogeneity of individual DMUs by including efficiency effects (i.e. DMU specific characteristics and environmental variables) in the model. Consequently, two different models are employed in thesis.

3.3.1 Model without Efficiency Effects

First, following model by Battese and Coelli (1992) that does not incorporate efficiency effects is examined. It follows on from Equation 3.6, where:

$$u_{it} = u_i exp(-\eta(t-T)) \tag{3.7}$$

the u_i are non-negative random variables which are assumed to account for efficiency in production and are assumed to be iid as truncations at zero of $N(\mu, \sigma_u^2)$; η is a parameter to be estimated.

For estimation, Battese and Coelli (1992) propose maximum likelihood estimation. The likelihood function is expressed in terms of the variance parameters:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \quad and \quad \gamma = \frac{\sigma_u^2}{\sigma^2} \tag{3.8}$$

3.3.2 Model with Efficiency Effects

Second, Battese and Coelli (1995) introduced model that assumes time-varying efficiency and allows to account for efficiency effects. It has the form of Equation 3.6, where:

$$u_{it} = \boldsymbol{z_{it}\delta} + w_{it} \tag{3.9}$$

Term $\boldsymbol{z_{it}}$ is M $\times$ 1 vector of explanatory variables associated with technical inefficiency of production of DMUs over time, and $\boldsymbol{\delta}$ is M $\times$ 1 vector of unknown coefficients. Variable w_{it} is defined by the truncation of the normal distribution with zero mean and variance, σ^2, such that the point of truncation is $-\boldsymbol{z_{it}\delta}$, i.e. $w_{it} \geq -\boldsymbol{z_{it}\delta}$. These assumptions are consistent with u_{it} being a non-negative truncation of the $N(\boldsymbol{z_{it}\delta}, \sigma^2)$.

Similarly to Battese and Coelli (1992) model estimation, maximum likelihood is employed. It enables simultaneous (one-stage) estimation of the parameters of both the stochastic frontier and the model for technical efficiency effects. It has been demonstrated in many pieces of work that one-stage estimation produces more efficient and unbiased results compared to two-stage estimation (Rosko and Mutter, 2008).

3.3.3 Efficiency Estimates

According to Coelli et al. (2005) the efficiency of production of the i-th DMU at time t relative to Equation 3.6 is defined as[11]:

$$e_{it} = \frac{E(C_{it}|u_{it}, \boldsymbol{Y_{it}})}{E(C_{it}|u_{it}=0, \boldsymbol{Y_{it}})} = exp(u_{it}) \tag{3.10}$$

For cost function, Equation 3.10 represents inefficiency rather than efficiency[12]. Consequently, Equation 3.10 is transformed in the following way:

$$0 < EFF_{it} = \frac{1}{e_{it}} \overset{(3.10)}{=} \frac{1}{exp(u_{it})} < 1 \tag{3.11}$$

Values of efficiencies now fall into the range between 0 and 1, where 1 is the highest possible efficiency.

[11] Both for Cobb-Douglas and Translog

[12] By definition, with larger departure from the estimated frontier, i.e. for increasing u_{it}, efficiency decreases; but e_{it} increases in Equation 3.6

4 Dataset

The data comprise information on **general practitioners (GPs)** operating in the Czech Republic. GPs were observed for three years; from 2015 to 2017. The panel data are unbalanced.

The data was provided by a private firm that operates a network of HC practices. HC is provided by the network to approximately 150000 patients per year and is funded by public health insurance.

The initial sample included 141 DMUs that were observed in at least one year. However, DMUs that did not solely specialize in the general practice were excluded to preserve homogeneity of the sample. The final sample includes 113 GPs where 70 of them provide HC to adults and 43 of them to children and youth. GPs were included in the sample even if they were not observed over the whole year[13]. This should not cause any problems in the SFA as low number of HC outputs of GPs is accordingly matched by lower total costs in particular year. In Table 4.1, there is a summary of the number of observations in each year.

The data about environment of GPs were collected from both the Czech Statistical Office and the Information service provided by Ministry of the Interior in the Czech Republic. In total, GPs from the examined sample work in 79 different municipalities in the Czech Republic.

Table 4.1: Number of Observations

GP	2015	2016	2017
Total	94	100	113
Children	34	38	43
Adult	60	62	70

[13]Some GPs were acquired/dispossessed within a given year, but not necessarily at the beginning/end of the year

4.1 Inputs

Total costs are used as the only input-variable in the regression. Employing total costs as the dependent variable in the SFA in HC at meso-level is fairly common (Hollingsworth, 2008). To our knowledge, there is only one such work in primary care (Puig-Junoy and Ortún, 2004).

Total costs of DMUs were observed over the period of three years and only nominal values were collected. Consequently, they were adjusted for inflation based on CPI of the Czech Republic[14]. In Table 4.2, there is a summary of deflated total costs of the whole sample over the period 2015-2017.

Table 4.2: Descriptive Statistics - Total Costs

Year	Mean	Median	Min.	Max.	St. Dev.
2015	1588150	1587072	275727	2639603	407468
2016	1752128	1720461	578498	2745528	367966
2017	1834556	1820764	220434	3107265	461711

Note: Rounded to the nearest integer

4.2 Outputs

Ideally, the variables of outputs in HC are health outcomes, i.e. the impact of a medical intervention on health status of a patient. However, this measure is not available in the Czech health system yet. Consequently, proxy variables for health outcomes are employed in the form of HC activities of GPs. This adjustment is consistent with available literature and is described in Chapter 2. Generally, HC activities are aggregated to a certain level and are divided into different categories in HC efficiency analyses. For instance, number of immunizations (Szczepura et al., 1993) number of patients seen (Laberge et al., 2016), number of prescriptions (Pai et al., 2000), etc.

[14] Average inflation for years 2015, 2016 and 2017 was employed for deflating total costs

Our dataset includes detailed information about HC activities of each practice. These activities can be divided into two broad categories based on the remuneration scheme. First category includes HC activities that are covered by lump-sum capitation payment that a GP receives for each registered patient; it is referred to as **Capitation Outputs (COs)** in the thesis. Second category consists of HC procedures that are remunerated by fee-for-service, i.e. a GP gets paid for each procedure performed. Thesis refers to this group as **Non-Capitation Outputs (NCOs)**. There is a list of both COs and COs in Table A2.5 and A2.6.

There is a major problem regarding COs. GPs do not record all activities from this category. The estimate of the firm is around 50% of COs, in terms of frequency of medical activities, is reported about. They were initially included in the SFA, however, the vast majority of them were statistically insignificant. Therefore, all COs, which represent 30 out of 138 different outputs in the dataset, were excluded from the analysis. This is a significant intervention into the dataset as COs represent large proportion of all outputs performed by GPs (Alexa et al., 2015). In order to at least partially account for COs in the SFA, proxy variable **Size** was utilized. It represents number of patients registered at a GP in a given year. The reasoning behind including this variable is that the majority of COs are costless in terms of material used and they affect total costs (dependent variable in the SFA) mostly through wages paid to the GPs. In other words, a GP gets paid for COs, regardless of the frequency of such outputs, by lump sum payment for each registered patient. Unfortunately, there was no way to account for the time devoted to performing COs in the analysis.

NCOs are fully recorded. In order to deal with high dimensionality of them, Principal Component Analysis is employed and Principal Components are used in the SFA. This approach and choice of components is described in Chapter 5. The use of Principal Componentss is associated with one significant drawback. The coefficients of PCs in the regression cannot be interpreted in any way as each component is comprised of different outcomes.

However, the primary focus of the SFA is on residual, which represents the inefficiency (Jacobs et al., 2006). Therefore, the magnitudes of estimated coefficients of PCs are not vital.

Table 4.3 summarizes total number of outputs performed in each year.

Table 4.3: Descriptive Statistics - Outputs of GPs

Year	Mean	Median	Min.	Max.	St. Dev.
2015	10220	9438	1568	27528	5345
2016	10516	9871	954	24070	5195
2017	10415	9285	344	25022	5372

Note: Rounded to the nearest integer

4.3 Efficiency Effects

Part of the SFA in the thesis is devoted to examining heterogeneity in the sample that might affect efficiency of GPs. It arises from both **environmental factors** and **specific characteristics** of individual GPs (Hjalmarsson et al., 1996). The model by Battese and Coelli (1995) can incorporate efficiency effects and is employed frequently in HC efficiency analyses (Rosko and Chilingerian, 1999; Zuckerman et al., 1994). To our knowledge, the model is not used in any primary care efficiency analysis[15]. Instead, it is accounted for heterogeneity by restricting comparison only to entities operating within a similarly constrained environment, e.g. in Pai et al. (2000), or Ramírez-Valdivia et al. (2011). There are three efficiency effects variables employed in the thesis.

First efficiency effect takes into account **competition** in a municipality of a GP. Generally, in HC, the number of DMUs of the same nature is employed as a proxy for competition (Zuckerman et al., 1994). Since this information is not available for GPs, the ratio of patients registered at the GP in a given year to the population of municipality[16] where a GP operates

[15]This model requires panel data; in available literature, SFA exploits only cross-sectional data in primary care

[16]For GPs providing HC to adults/children, only adult/children population is take into account

is used instead. The ratio can be higher than 100 % as GP in one municipality can provide HC to patients from different municipalities. It is assumed, that the higher is the ratio the less competitors are present in a given municipality. From microeconomic theory, competition serves as incentive for efficiency improvement, thus negative impact of this proxy variable on efficiency is expected.

Second efficiency effect is a dummy variable that represents **rural** municipality. There are several definitions of what is considered as a rural municipality. According to the Municipalities Act in the Czech law (Paragraph 3), rural municipality have population lower than 3000. This criterium is employed in the thesis. Negative impact of rural environment on efficiency is expected as poorer living conditions, and thus more costly health treatment, are assumed in rural areas.

Last, there are two specializations within the sample of GPs in the sample. GPs that provide HC to children and youth; and to adults. Hence, dummy variable for **adult specialization** is employed in the analysis. It is presumed that children require more costly and time demanding health treatment than adult population, and thus GPs specializing in adult HC are expected to be more efficient.

The descriptive statistics of determinants of efficiency is in Table 4.4. The values stated are over the whole period 2015-2017.

Table 4.4: Descriptive Statistics - Determinants of Efficiency

Year	Mean	Median	Min.	Max.	St. Dev.
Region	0.486	0.137	0.001	3.553	0.776
Rural	0.137	0	0	1	0.344
Adult	0.629	1	0	1	0.484

Note: Descripiton of the variable names is in Table A1.1

5 Principal Component Analysis

Principal Component Analysis (PCA) was introduced by Pearson (Pearson, 1901). It is a statistical procedure that converts a set of observations of possibly correlated variables into variables called Principal Components (PCs), which are linearly uncorrelated. The total number of PCs relates to either the number of initial variables or the number of observations minus one[17]. PCs are ranked by how much variance of data each PC captures, i.e. the first PC captures the most variance of data. Such variance is expressed by eigenvalue that is based on the correlation matrix of the dataset. Usually, only small number of PCs explain large proportion of the total variance of the data.

PCA is applied to NCOs variables for following reasons. First, there is a great number of different NCOs in the dataset. Including all of them in the regression as individual variables would significantly decrease degrees of freedom. The aim of the analysis is to keep as much information from the dataset as possible, hence, application of PCA is desirable. Second, some NCOs are highly correlated, and thus multicollinearity among them would undermine the statistical significance of the corresponding estimated coefficients.

The first 5 PCs are taken into account in the SFA. They explain approximately 76 % of the total variance of NCOs which is satisfactory (Figure A1.1). The summary of them is in Table 5.1.

One major adjustment had to be made regarding PCs. Since each observation is expressed in terms of coordinates in relation to PCs, negative values occur in the dataset. Both Cobb-Douglas and Translog include logged independent variables, hence, PCs were shifted by a constant A:

$$A = min(PC_{jit}) + 1; \quad \jmath = 1, ..., J; \quad i = 1, ..., N; \quad t = 1, ..., T \tag{5.1}$$

Where PC_{jit} is a coordinate of the i-th DMU at time t related to j-th principal component.

[17] Former is chosen if it is smaller than latter and vice versa

All coordinates are now greater or equal than 1 and PCs can be logged. This adjustment does not cause any problems in further analysis as the variance of PCs remains the same (only mean is shifted).

Table 5.1: Summary of PCA

	Eigenvalue	Variance	Cumulative Var.
PC 1	200,928.8	28.822	28.822
PC 2	139,074.8	19.95	48.772
PC 3	111,444.9	15.986	64.759
PC 4	43,444.94	6.232	70.991
PC 5	35,637.54	5.112	76.103

Note: Values of variance are expressed in percentages with respect to total variance of the sample

6 Empirical Results

This section is devoted to the description of empirical results of the Stochastic Frontier Analysis. It follows the order of Chapter 3. There were two different models employed; both assume time-varying efficiency. First model omits efficiency effects, whereas, second model includes efficiency effects to account for heterogeneity among GPs in the sample. Eventually, there is a discussion of results of the SFA.

6.1 Model without Efficiency Effects

Model by Battese and Coelli (1992) is employed and has the following form:

$$\begin{gathered} log(TC_{it}) = log(Size_{it}) + log(PC1_{it}) + log(PC2_{it}) + \\ + log(PC3_{it}) + log(PC4_{it}) + log(PC5_{it}) + v_{it} + u_{it} \end{gathered} \tag{6.1}$$

Initially, both Cobb-Douglas and Translog functional forms were considered. Likelihood Ratio test[18] was carried out to decide between these specifications. Although, Translog has desirable property of flexibility, Cobb-Douglas functional form was chosen based on the results of the test. Furthermore, Cobb-Douglas saves degrees of freedom by eliminating the cross-product and squared terms present in Translog function.

Equation 6.1 can employ several distributions of inefficiency. Based on the Likelihood Ratio test, truncated-normal distribution was chosen over half-normal distribution. Furthermore, model with efficiency effects can employ only truncated normal distribution, it is therefore desirable to use the same distributions in both models when they are compared.

Before the SFA was carried out, presence of inefficiency was tested. Again, Likelihood Ratio test was employed and model with inefficiency, estimated by MLE, had significantly higher loglikelihood value than model without inefficiency, which was estimated by OLS. Hence, efficiency is assumed to be present in the production process of GPs.

[18]Generally, the test statistic employed in the thesis for Likelihood Ratio test has following form: $2 \times [logLikelihoodValue(M1) - logLikelihoodValue(M2)]$. Where M1 is unrestricted model and M2 is a restricted model

In Table 6.1, there are estimated coefficients of the model. The Principal Components are all significant but the corresponding coefficients cannot be interpreted in any way. In terms of other coefficients, the number of patients registered in a given year has a positive effect on total costs. In particular, on average, if the number of patients increases by 1 % the total cost increase by approximately 0.14 %. The estimated intercept is positive and is statistically significant which makes sense as there are some fixed costs involved for each GP.

Table 6.1: Estimated Coefficients - Model without Efficiency Effects

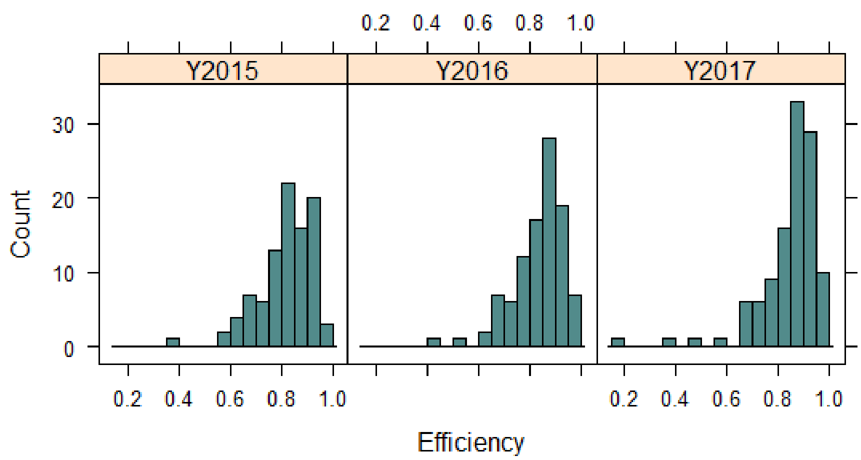
	Estimate	Std. Error	z value	Pr(>|z|)
β_0	7.827	1.016	7.704	$***$
log(Size)	0.139	0.039	3.531	$***$
log(PC1)	0.209	0.079	2.652	$**$
log(PC2)	0.099	0.026	3.737	$***$
log(PC3)	0.536	0.066	8.133	$***$
log(PC4)	0.201	0.095	2.116	$*$
log(PC5)	-0.265	0.097	-2.743	$**$
σ^2	0.313	0.062	5.082	$***$
γ	0.934	0.019	48.271	$***$
η	0.137	0.043	3.223	$**$

Note: *** ($p < 0.01$), ** ($p < 0.05$) *and* * ($p < 0.1$)

Time variable (η) is statistically significant and has a positive effect on efficiency. It supports the initial assumption that efficiency varies across time. The estimate for the variance parameter γ is close to one, which indicates that variance of inefficiency takes large part of total variance of composite error term. Z statistic is not reliable for the statistical significance of the estimated parameters, as parameter σ^2 is lef-censored and parameter γ is both right-censored and left-censored. Moreover, the standard errors of additional parameters, such as variance of white noise and variance of inefficiency, are obtained by delta method which might provide poor approximation of the true standard errors (Coelli et al., 2005).

A summary of estimated efficiency is in Table A1.2. The mean efficiency of the whole sample of GPs is approximately 83.4 % over the whole period. Year-on-year mean and median efficiency increased which corresponds to positive estimated coefficient of the time variable. Figure 6.1 shows a histogram of efficiency distribution in each year. The list of both individual efficiencies of GPs and their ranks is in Table A2.1 and A2.3. It is worth pointing out, that the rank of the of GPs changes over time very slightly, most likely due to unbalanced structure of the panels. This scenario arises from the definition of the efficiency term in Equation 3.7 which assumes that individual efficiencies in the sample change in the same pattern over time. This is supported by the fact, that Spearman Rank Correlation coefficients in Table 6.3 are equal to unity among the time periods.

Figure 6.1: Histogram of Individal Efficiencies - Model without Efficiency Effects



6.2 Model With Efficiency Effects

Model by Battese and Coelli (1995) is employed. It has the form of Equation 6.1 where:

$$u_{it} = Rural_{it} + Region_{it} + Adult_{it} + w_{it} \tag{6.2}$$

Cobb-Douglas functional was employed due to the same reasons as in the previous model. Truncated normal distribution is the only possible distribution of efficiency in the model that incorporates efficiency effects. Likelihood ratio test was performed to prove presence of inefficiency; model with no inefficiency was ruled out based on the results of the test.

As in the previous case, all PCs and the intercept are statistically significant. The Size variable is significant as well, however the magnitude of the coefficient is slightly lower than in the previous model. In this case, on average, with 1 % increase of registered patients at a GP in a given year the total costs increase by 0,062 %. The estimate for the variance parameter γ is close to one, which indicates the inefficiency effects are likely to be highly significant in the analysis of the value of total costs of the GPs. The estimated coefficients of efficiency effects are of particular interest in this model. All of them are statistically significant.

Rural dummy variable has the largest effect on inefficiency. According to the corresponding estimated coefficient, GPs that are situated in rural municipalities are more inefficient than those situated in urban areas. It coincides with the initial hypothesis.

Negative impact on inefficiency is attributed to the dummy variable **Adult**. In other words, GPs that provide HC to children and youth are more inefficient than GPs that provide healthcare to adults. Again, this is consistent with the initial hypothesis that adults are generally less demanding patients, both timewise and costwise, than children.

The estimated coefficient of **Region** variable is negative, which indicates that the larger is the region coverage of a GP, i.e. less competition in a given municipality, the less inefficient the GP is. This estimation contradicts

Table 6.2: Estimated Coefficients - Model with Efficiency Effects

	Estimate	Std. Error	z value	Pr(>|z|)
β_0	8.775	0.929	9.444	$***$
log(Size)	0.062	0.031	2.016	$***$
log(PC1)	0.255	0.057	4.494	$***$
log(PC2)	0.141	0.019	7.395	$***$
log(PC3)	0.465	0.057	8.128	$***$
log(PC4)	0.219	0.069	3.158	$**$
log(PC5)	-0.355	0.081	-4.403	$***$
Rural	0.790	0.268	2.944	$**$
Region	-0.00300	0.00142	-2.120	$*$
Adult	-0.431	0.207	-2.085	$*$
σ^2	0.145	0.026	5.532	$***$
γ	0.909	0.026	34.833	$***$

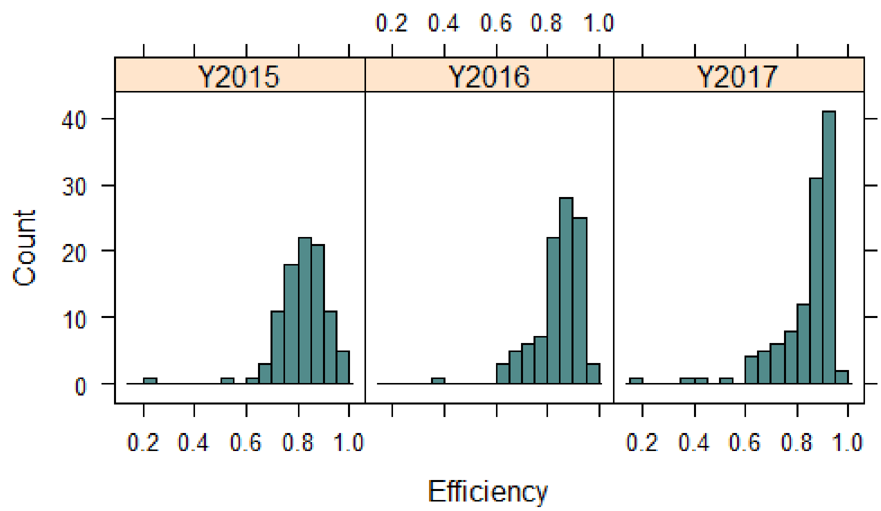
Note: *** ($p < 0.01$), ** ($p < 0.05$) *and* * ($p < 0.1$)

the initial presumption that efficiency is encouraged by higher competition in a municipality. The significance and sign of the coefficient could be attributed to the fact, that wages are set by the company. In particular, company might offer higher wages to GPs that operate in municipality with higher competition. Consequently, total costs of the GPs rise which might create room for inefficiency. However, this is just speculation as the wage policy of the company was not revealed to us.

Descriptive statistics of estimated efficiency is in Table A1.2. The mean efficiency of the whole sample of GPs is approximately 83.3 %. Even though mean efficiency decreases from year 2016 to 2017, year-on-year median efficiency increases. Figure 6.2 demonstrates the distribution of individual efficiencies in each year. In the first year, the distribution of efficiencies is close to normal distribution. In the following years, left-skewed distribution demonstrates that individual GPs tend to approach maximum efficiency. The predetermined truncated normal distribution is imposed on the entire set of individual efficiencies, hence, variation in distributions is possible among individual years.

The list of individual efficiencies is in table in Table A2.2 and A2.4. In this case, the ranks of individual GPs intertemporally differ quite substantially. This is reflected in Spearman Rank Correlation Coefficient in Table 6.3 which is considerably low.

Figure 6.2: Histogram of Individal Efficiencies - Model with Efficiency Effects



6.3 Discussion

In this section, the outcomes of the model without efficiency effects (M1) and model with efficiency effects (M2) are compared. Furthermore, shortcomings of results of the SFA are discussed

Both models employ Cobb-Douglas functional form and assume time-varying efficiency. They differ in the specification of the inefficiency term which influences the results of corresponding models.

M1 relies on the assumption that efficiency of GPs evolves in the same pattern over time. On the other hand, M2 lets the efficiency effects determine the magnitude and direction of change of individual efficiencies over time. In terms of median efficiency in each year, both models indicate that time has positive impact on efficiency. In M1, it is supported by the positive estimated coefficient and significance of time variable (η). Therefore, we can conclude that efficiency of the sample of GPs improves over time. In M2, the γ parameter is slightly lower which signifies that variance of white noise takes up a slightly larger part of total variance than in M1.

Table 6.3: Spearman Rank Correlation Matrix of Efficiency Scores

	M1				**M2**			
	2015	2016	2017	Mean	2015	2016	2017	Mean
2015	1							
2016	1	1						
2017	1	1	1					
Mean	1	1	1	1				
2015	**0.778**	0.778	0.778	0.778	1			
2016	0.776	**0.776**	0.776	0.776	0.524	1		
2017	0.789	0.789	**0.789**	0.789	0.505	0.670	1	
Mean	0.942	0.942	0.942	**0.942**	0.801	0.818	0.856	1

Note: M1 = Model without Efficiency Effects, M2 = Model with Efficiency Effects

The descriptive statistics indicates, that both M1 and M2 produce very similar results. The mean efficiency of the whole sample is almost identical. However, Spearman Rank Correlation coefficients for individual years of the corresponding models (bold coefficients in Table 9) are all equal to approximately 0.78. Hence, accounting for heterogeneity (M2) influences the rank and values of individual efficiencies.

Both models rely on strong assumptions about distribution of the inefficiency term. It has been shown in literature, that the choice of distribution of the inefficiency term affects values of inefficiency (Jacobs et al., 2006). It is therefore very likely, that different models with different distributions of the inefficiency term would produce different results. According to Rosko and Mutter (2008), these differences are only marginal[19].

Furthermore, apart from the exogeneity of the inefficiency term, both M1 and M2 readily assume that the variance of the efficiency term is homoscedatic. Alternative models have been proposed, such as Caudill and Ford (1993) or Wang (2002), that allow heteroscedacity in the truncated normal distribution and obtain more consistent results. However, this thesis follows the conventional literature on measuring efficiency in HC where the models by Battese and Coelli (1992, 1995) are still most widely employed, and thus heteroscedacity of the efficiency term is neglected in the analysis.

Another limitation of the analysis is the possibility of omitted variables in the specification of the inefficiency term. Specifically, more characteristics of individual GPs, such as composition of their patients or work experience, could be employed. Unfortunately, this information was not available. Furthermore, neither of the models incorporates quality of the outputs of GPs. We were not able to identify a comprehensive measure of quality in our dataset and therefore quality of HC was not directly assessed in the analysis. Consequently, the more HC activities a GP performs for given level of total costs the more efficient she is, regardless of the impact on the health of the patients to whom is HC provided.

[19]They compare models with both Cobb-Douglas and Translog functions that incorporate truncated, half-normal and truncated normal distribution.They are used on the same sample; at maximum, mean efficiency differs by 5 percentage points and Spearman Correlation coefficient by 0,17.

Conclusion

The purpose of the thesis is to assess performance of general practitioners (GPs) in the Czech Republic. It analyses technical efficiency of 113 GPs over the period 2015-2017 using the Stochastic frontier analysis (SFA).

The SFA exploits unique dataset that consists of information about individual outputs and total costs of the sample of GPs. Principal Component Analysis was utilized to deal with the high dimensionality of outputs. Consequently, 5 Principal Components were used in the regressions as independent variables. Two different models were employed in the SFA to demonstrate how efficiency of GPs changes over time. Even though GPs are considerably homogenous sample, they operate in different environment. Therefore, the second model accounts for environmental constraints by including variables (efficiency effects) that represent rural/urban municipality and the amount of competition that each GP faces. Furthermore, dummy variable that distinguishes adult GPs from children GPs is used as the third efficiency effect.

The results of the SFA indicate that the mean efficiency of the GPs is approximately 83 %. According to both models, median efficiency improves over time. Examined efficiency effects were proved to be significant in determining efficiency of GPs. In particular, rural environment has negative impact on efficiency, GPs that provide HC to adults are more efficient and competition discourages efficiency.

Outcomes of the models should be taken with caution. The analysis suffers from several limitations, such as strong assumptions about the distribution of efficiency term and omitting quality variables from the models. Furthermore, technical efficiency does not provide the whole picture about the performance of GPs. It relates to cost-effectiveness of GPs rather than effectiveness in taking care of patients' health. In addition, obtained results refer to **relative** technical efficiency which is specific to the sample exploited in the analysis, and thus, one should take that into consideration when comparing them to different studies with different samples.

The thesis is a pioneer in the area of efficiency measurement of Czech GPs and it brings the first insight into the problem. By no means the thesis aims to pursue any policy changes in the Czech health system. It provides rather incomplete overview of performance of GPs and encourages further research in this area. Subsequent analyses should exploit longer-time span, include more environmental and quality variables, should the data be available. Other efficiency measurement approaches, such as conditional DEA may be tested as well. Furthermore, development of efficiency methods and both collection and provision of information about medical activities of GPs and their consequent impact on health of patients could significantly contribute to measurement of performance of GPs in the Czech Republic.

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Appendix 1

Table A1.1: Description of Variables

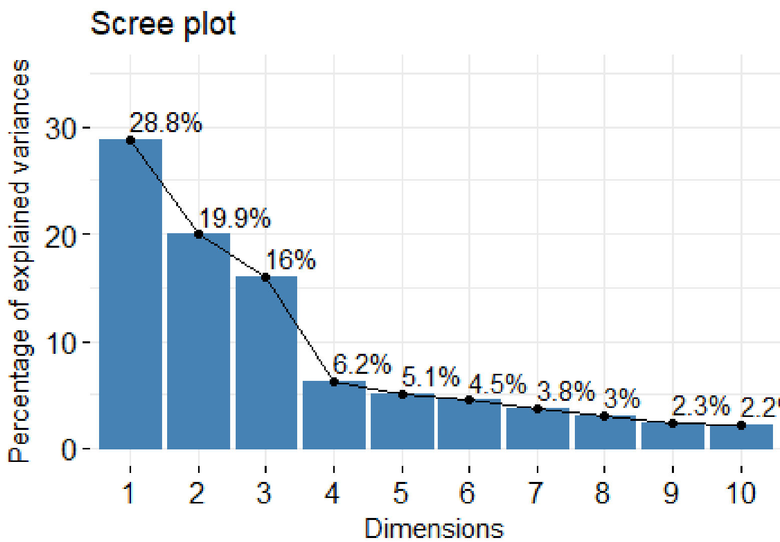
Variable	Description
	Stochastic Frontier Variables
TC	Total costs of GPs in a given year adjusted for inflation
Size	Number of registered patients of GPs in a given year
PC1	First principal component
PC2	Second principal component
PC3	Third principal components
PC4	Fourth principal component
PC5	Fifth principal component
	Efficiency Effects Variables
Adult	Dummy indicating adult specialization of GPs
Region	Ratio of number of regitsered patients to population of a municipality
Rural	Dummy indicating rural municipality of GPs

Table A1.2: Descriptive Statistics - Efficiency Estimates

	2015	2016	2017
Without Efficiency effects			
Min.	0.3832	0.4332	0.1652
Median	0.8376	0.8577	0.8724
Mean	0.8171	0.8374	0.8449
St.dev.	0.1053	0.0984	0.1186
Max.	0.9734	0.9767	0.9796
With Efficiency effects			
Min.	0.2067	0.3983	0.1619
Median	0.8256	0.8563	0.8727
Mean	0.8171	0.8418	0.8382
St.dev.	0.1033	0.0932	0.1262
Max.	0.9671	0.9582	0.9646

Note: Rounded to three decimal places

Figure A1.1: Scree Plot of the First 10 PCs



Appendix 2

Table A2.1: M1-Individal Efficiencies and Ranks (A)

DMU	2015	*Rank*	2016	*Rank*	2017	*Rank*
8AD01A001	0.871	30	0.887	33	0.900	38
8AD01A002	0.808	60	0.830	65	0.850	73
8AD02A004	0.922	18	0.931	19	0.940	19
8AD04A001	0.693	83	0.726	88	0.757	97
8AD04A002	0.645	89	0.682	94	0.716	103
8AD04A003	0.946	5	0.953	5	0.959	5
8AD04A004	0.939	10	0.946	10	0.953	10
8AD05A001	0.766	70	0.793	75	0.816	83
8AD08A001					0.935	21
8AD08A002					0.929	23
8AD08A003					0.685	106
8AD08A004					0.653	109
8AD08A005					0.925	28
8AD08A006					0.808	87
8BD03A009	0.812	56	0.834	61	0.853	69
8BD06A001	0.943	9	0.950	9	0.956	9
8BD07A001			0.917	23	0.927	25
8BD09A001					0.921	29
8GD04A006	0.965	3	0.969	3	0.973	3
9AA00A428	0.915	20	0.925	21	0.934	22
9AA00A445	0.766	71	0.792	76	0.816	84
9AA01A097	0.875	28	0.890	31	0.903	36
9AA02A550	0.775	66	0.800	71	0.823	79
9AA02A635	0.839	46	0.858	50	0.875	55
9AA03B047	0.849	42	0.867	46	0.882	51
9AA04A318	0.583	93	0.625	98	0.664	108
9AA06A009	0.866	35	0.882	39	0.896	44
9AA06A249	0.744	75	0.773	80	0.799	89
9AA06A358	0.697	82	0.730	87	0.759	96
9AA06A501	0.826	51	0.846	55	0.864	62
9AA07A083	0.883	26	0.897	29	0.910	34
9AA07A298	0.808	59	0.830	64	0.850	72
9AA07A553	0.590	92	0.631	97	0.669	107
9AA07A739			0.537	99	0.581	110
9AA07A822	0.785	63	0.810	68	0.831	76
9AA07B080	0.835	50	0.854	54	0.871	59
9AA07B312	0.772	67	0.798	72	0.821	80
9AA07B336	0.743	76	0.772	81	0.797	90
9AA07F610	0.860	36	0.877	40	0.891	45
9AA07F828					0.371	112
9AA09A149	0.932	11	0.940	11	0.947	11
9AA09A246	0.966	2	0.971	2	0.974	2
9AA10B168	0.764	72	0.791	77	0.815	85
9AA11A880	0.770	68	0.796	73	0.820	81
9AA12A894	0.943	7	0.950	7	0.957	7
9AA12A971	0.839	47	0.858	51	0.875	56
9AA12F369	0.943	8	0.950	8	0.956	8
9AA13B066	0.770	69	0.796	74	0.819	82
9AA13B651	0.788	62	0.813	67	0.834	75
9AA13B961	0.815	55	0.836	60	0.856	68
9AA13C240	0.750	74	0.778	79	0.803	88
9AA13D612	0.648	88	0.685	93	0.719	102

Note: M1 = Model without Efficiency Effects

Table A2.2: M2-Individal Efficiencies and Ranks (A)

DMU	2015	*Rank*	2016	*Rank*	2017	*Rank*
8AD01A001	0.887	19	0.850	55	0.890	48
8AD01A002	0.830	45	0.841	64	0.852	72
8AD02A004	0.917	13	0.930	11	0.888	50
8AD04A001	0.821	50	0.827	70	0.641	107
8AD04A002	0.814	53	0.634	97	0.857	69
8AD04A003	0.954	3	0.875	42	0.907	32
8AD04A004	0.923	10	0.902	28	0.932	21
8AD05A001	0.731	83	0.881	38	0.870	61
8AD08A001					0.947	5
8AD08A002					0.947	6
8AD08A003					0.649	106
8AD08A004					0.626	108
8AD08A005					0.937	14
8AD08A006					0.739	96
8BD03A009	0.790	62	0.853	53	0.810	86
8BD06A001	0.953	4	0.924	16	0.877	54
8BD07A001			0.927	13	0.905	34
8BD09A001					0.930	22
8GD04A006	0.965	2	0.958	1	0.938	12
9AA00A428	0.764	71	0.947	5	0.878	53
9AA00A445	0.856	33	0.846	60	0.751	94
9AA01A097	0.824	48	0.857	50	0.873	57
9AA02A550	0.711	88	0.903	27	0.905	35
9AA02A635	0.866	31	0.884	37	0.870	60
9AA03B047	0.850	36	0.896	30	0.856	70
9AA04A318	0.631	92	0.938	8	0.505	110
9AA06A009	0.804	56	0.921	20	0.872	58
9AA06A249	0.717	86	0.777	82	0.782	88
9AA06A358	0.899	17	0.732	86	0.788	87
9AA06A501	0.754	76	0.887	33	0.927	23
9AA07A083	0.905	16	0.896	31	0.874	56
9AA07A298	0.802	58	0.852	54	0.904	36
9AA07A553	0.774	67	0.614	98	0.615	109
9AA07A739			0.398	100	0.921	26
9AA07A822	0.791	61	0.850	56	0.863	66
9AA07B080	0.774	68	0.876	41	0.890	49
9AA07B312	0.823	49	0.776	83	0.868	64
9AA07B336	0.737	82	0.840	65	0.767	90
9AA07F610	0.877	29	0.831	69	0.907	31
9AA07F828					0.355	112
9AA09A149	0.950	5	0.897	29	0.895	47
9AA09A246	0.967	1	0.940	6	0.954	2
9AA10B168	0.757	75	0.821	75	0.817	83
9AA11A880	0.801	59	0.861	49	0.855	71
9AA12A894	0.919	11	0.948	4	0.943	8
9AA12A971	0.827	47	0.870	44	0.901	41
9AA12F369	0.936	7	0.922	18	0.947	4
9AA13B066	0.805	55	0.796	79	0.880	52
9AA13B651	0.774	69	0.848	58	0.864	65
9AA13B961	0.747	81	0.864	48	0.883	51
9AA13C240	0.713	87	0.805	77	0.923	24
9AA13D612	0.749	79	0.713	90	0.721	100

Note: M2 = Model with Efficiency Effects

Table A2.3: M1-Individal Efficiencies and Ranks (B)

DMU	2015	*Rank*	2016	*Rank*	2017	*Rank*
9AA14B184	0.925	16	0.934	17	0.942	17
9AA16B674	0.728	77	0.757	82	0.785	91
9AA19B913	0.855	38	0.872	42	0.887	47
9AA20B741	0.867	34	0.883	38	0.897	43
9AA20C728	0.925	15	0.934	16	0.942	16
9AA22B806	0.906	21	0.917	22	0.927	24
9AA23C339	0.870	33	0.885	37	0.899	41
9AA23D467	0.890	24	0.904	26	0.915	30
9AA23D980	0.870	32	0.885	36	0.899	40
9AA23F385	0.703	80	0.735	85	0.764	94
9AA23F466	0.841	44	0.860	48	0.876	53
9AA23F674					0.915	31
9AA23F708			0.898	28	0.910	33
9AA24C297	0.810	58	0.832	63	0.851	71
9AA25C911	0.825	52	0.845	56	0.863	63
9AA26C589					0.867	61
9AA27C608	0.719	78	0.750	83	0.778	92
9AA27C660	0.836	49	0.855	53	0.872	58
9AA33D461	0.931	13	0.940	13	0.947	13
9AA33E360	0.929	14	0.938	14	0.945	14
9AI03A598	0.621	90	0.659	95	0.695	104
9AI03A846	0.619	91	0.658	96	0.694	105
9AI03F618	0.973	1	0.977	1	0.980	1
9BA03A126	0.932	12	0.940	12	0.947	12
9BA05A490	0.785	64	0.809	69	0.831	77
9BA06B287	0.840	45	0.859	49	0.875	54
9BA07A016	0.658	85	0.694	90	0.727	99
9BA07A381	0.764	73	0.790	78	0.814	86
9BA07A489	0.850	40	0.867	44	0.883	49
9BA07B082	0.652	87	0.689	92	0.722	101
9BA07F627	0.945	6	0.952	6	0.958	6
9BA07F632	0.876	27	0.891	30	0.904	35
9BA07F641	0.823	53	0.844	57	0.862	64
9BA07F696			0.885	35	0.899	42
9BA09A370	0.820	54	0.841	59	0.859	66
9BA09A615	0.849	41	0.867	45	0.883	50
9BA14B139	0.924	17	0.933	18	0.941	18
9BA16B595					0.858	67
9BA16B708	0.383	94	0.433	100	0.482	111
9BA17B512	0.700	81	0.732	86	0.762	95
9BA17B513	0.917	19	0.927	20	0.936	20
9BA17C134	0.811	57	0.833	62	0.853	70
9BA18C279	0.875	29	0.890	32	0.903	37
9BA19D960	0.775	65	0.800	70	0.823	78
9BA21C326	0.665	84	0.700	89	0.733	98
9BA22C031	0.858	37	0.875	41	0.890	46
9BA22C884	0.654	86	0.690	91	0.724	100
9BA23C593	0.800	61	0.823	66	0.844	74
9BA23F409	0.836	48	0.855	52	0.872	57
9BA23F681			0.843	58	0.861	65
9BA25C075	0.884	25	0.898	27	0.910	32
9BA25C734	0.950	4	0.956	4	0.962	4
9BA25C778	0.905	22	0.916	24	0.927	26
9BA26C585	0.847	43	0.865	47	0.881	52
9BA27D232	0.852	39	0.869	43	0.885	48
9BA32C825			0.936	15	0.943	15
9BA33F704					0.868	60
9BA33F808					0.165	113
9BA38D638	0.871	31	0.886	34	0.900	39
9BA38D641	0.903	23	0.914	25	0.925	27
9BI03A011	0.714	79	0.745	84	0.774	93

Note: M1 = Model without Efficiency Effects

Table A2.4: M2-Individal Efficiencies and Ranks (B)

DMU	2015	*Rank*	2016	*Rank*	2017	*Rank*
9AA14B184	0.881	26	0.953	3	0.941	9
9AA16B674	0.750	78	0.697	92	0.739	97
9AA19B913	0.752	77	0.925	14	0.902	40
9AA20B741	0.849	39	0.848	57	0.920	28
9AA20C728	0.932	8	0.921	19	0.933	19
9AA22B806	0.887	22	0.912	24	0.934	17
9AA23C339	0.850	38	0.910	25	0.938	11
9AA23D467	0.912	15	0.894	32	0.869	62
9AA23D980	0.819	52	0.886	34	0.937	13
9AA23F385	0.768	70	0.777	81	0.752	93
9AA23F466	0.786	64	0.907	26	0.947	7
9AA23F674					0.936	16
9AA23F708			0.869	45	0.903	38
9AA24C297	0.848	40	0.865	47	0.766	91
9AA25C911	0.848	41	0.838	68	0.850	75
9AA26C589					0.904	37
9AA27C608	0.761	72	0.826	72	0.774	89
9AA27C660	0.886	23	0.847	59	0.848	76
9AA33D461	0.898	18	0.919	21	0.934	18
9AA33E360	0.931	9	0.934	10	0.936	15
9AI03A598	0.757	73	0.677	96	0.699	101
9AI03A846	0.820	51	0.789	80	0.443	111
9AI03F618	0.944	6	0.958	2	0.965	1
9BA03A126	0.828	46	0.939	7	0.902	39
9BA05A490	0.793	60	0.707	91	0.833	80
9BA06B287	0.803	57	0.822	74	0.920	27
9BA07A016	0.665	91	0.612	99	0.657	104
9BA07A381	0.780	65	0.774	84	0.759	92
9BA07A489	0.879	28	0.916	22	0.901	42
9BA07B082	0.690	89	0.682	95	0.676	102
9BA07F627	0.918	12	0.937	9	0.933	20
9BA07F632	0.852	35	0.838	67	0.875	55
9BA07F641	0.870	30	0.825	73	0.871	59
9BA07F696			0.886	35	0.897	45
9BA09A370	0.845	42	0.811	76	0.837	78
9BA09A615	0.887	21	0.846	61	0.833	81
9BA14B139	0.915	14	0.924	17	0.869	63
9BA16B595					0.852	73
9BA16B708	0.207	94	0.729	87	0.651	105
9BA17B512	0.749	80	0.720	88	0.732	98
9BA17B513	0.884	24	0.913	23	0.922	25
9BA17C134	0.854	34	0.752	85	0.816	84
9BA18C279	0.805	54	0.805	78	0.907	33
9BA19D960	0.777	66	0.693	93	0.857	68
9BA21C326	0.542	93	0.878	40	0.851	74
9BA22C031	0.757	74	0.855	52	0.950	3
9BA22C884	0.722	84	0.682	94	0.728	99
9BA23C593	0.718	85	0.856	51	0.826	82
9BA23F409	0.831	44	0.838	66	0.814	85
9BA23F681			0.827	71	0.835	79
9BA25C075	0.788	63	0.871	43	0.846	77
9BA25C734	0.881	25	0.929	12	0.939	10
9BA25C778	0.880	27	0.880	39	0.910	30
9BA26C585	0.842	43	0.843	62	0.895	46
9BA27D232	0.887	20	0.884	36	0.673	103
9BA32C825			0.925	15	0.920	29
9BA33F704					0.861	67
9BA33F808					0.162	113
9BA38D638	0.850	37	0.842	63	0.898	44
9BA38D641	0.865	32	0.866	46	0.900	43
9BI03A011	0.685	90	0.716	89	0.744	95

Note: M2 = Model with Efficiency Effects

Table A2.5: Frequncy of Outputs (A)

Code	NCO	2015	2016	2017
00110	1	0	4	0
00121	1	18	38	88
00122	1	23	26	64
00123	1	1	2	4
01021	1	6, 884	6, 504	6, 316
01022	1	28, 130	23, 278	23, 399
01023	0	99, 571	91, 711	91, 895
01024	0	96, 417	76, 697	69, 743
01025	0	3, 172	2, 532	1, 992
01030	0	63, 873	71, 410	80, 811
01040	1	4, 185	3, 831	4, 125
01150	1	3, 825	4, 093	3, 837
01160	1	16	43	22
01170	1	14	9	4
01180	1	54	50	53
01185	1	1	0	0
01201	1	7, 112	3, 722	2, 143
01298	1	5	6	8
01299	1	30	27	14
01441	1	5, 252	3, 952	2, 527
01443	1	19, 567	15, 111	11, 627
01445	1	2, 681	1, 777	781
01999	1	18, 585	18, 809	15, 973
02021	1	3, 222	2, 633	1, 970
02022	1	20, 875	18, 061	13, 891
02023	1	30, 610	28, 301	21, 265
02024	1	13, 754	13, 260	10, 945
02031	1	1, 004	894	879
02032	1	12, 538	11, 558	9, 193
02033	1	33, 548	32, 921	24, 285
02034	1	13, 407	13, 905	10, 461
02100	1	59	70	96
02105	1	22, 548	20, 059	17, 957
02125	1	14, 204	13, 053	10, 058
02130	1	272	397	212
02200	1	263	332	281
02210	1	6	7	8
02220	1	1, 413	109	0
02222	1	1	0	0
02230	1	40, 914	32, 157	23, 425
02240	1	955	0	0
06111	0	92	126	46
06113	1	0	0	5
06115	1	4	0	2
06119	0	5	16	5, 107
06121	0	268	321	384
06123	0	648	435	470
06125	0	13	11	8
06127	0	1, 986	2, 509	1, 343
06129	0	0	1	2
06132	1	6	0	0
06135	1	0	0	1
06137	1	5	0	1
06145	1	1	2	1
06151	1	0	0	2
06323	1	5	1	2
09111	1	41, 549	32, 746	24, 406
09113	1	4	0	2
09115	1	21, 798	23, 819	19, 805
09117	1	3, 276	3, 204	2, 879
09119	1	45, 601	45, 023	41, 820
09123	1	24, 399	24, 308	20, 237
09125	1	135	103	33
09127	1	13, 175	8, 962	6, 568
09129	1	1	0	0
09131	1	0	0	2
09133	1	4, 110	4, 549	5, 556
09211	1	21	28	107
09213	1	7	4	1
09215	0	21, 918	21, 700	23, 654
09216	0	507	569	786
09217	0	4	3	5
09219	0	367	571	931

Note: Explanations to the codes of outcomes in www.vzp.cz

Table A2.6: Frequncy of Outputs (B)

Code	NCO	2015	2016	2017
09220	0	238	117	235
09221	0	0	1	0
09223	1	1, 272	1, 589	2, 168
09227	1	0	0	2
09233	0	19	35	32
09234	1	15	11	0
09235	0	38	33	36
09237	0	1, 629	1, 339	1, 577
09239	1	13	2	2
09241	1	469	350	296
09249	1	2	0	0
09251	1	0	3	0
09253	0	5	3	6
09507	0	111	97	48
09509	1	683	778	686
09511	0	110, 462	105, 161	104, 691
09513	0	8, 019	9, 137	9, 869
09521	1	14	25	53
09523	0	2, 219	3, 756	3, 463
09525	0	401	182	201
09527	1	42	26	47
09532	1	8, 327	5, 994	4, 843
09543	1	226, 634	187, 502	160, 466
09545	1	0	2	6
09547	1	7, 593	23, 458	18, 576
09550	1	20, 814	16, 906	15, 129
09551	1	19, 555	15, 875	14, 640
09555	1	0	1	3
11021	1	118	30	39
11022	1	904	930	977
11023	1	1, 125	829	745
11024	1	88	23	18
11110	1	1	0	0
11111	1	1, 356	1, 035	1, 102
12024	1	444	317	285
12130	1	1	1	1
13051	1	3	1	0
13101	1	1, 304	978	541
13102	1	204	67	44
13103	1	72	87	54
15120	1	10, 863	9, 102	8, 951
15121	1	954	591	461
17129	1	138	14	0
21113	1	684	631	179
21510	1	0	1	1
21520	1	0	0	10
25211	1	48	33	0
25235	1	338	285	150
27210	1	0	0	1
29510	1	7	29	36
29520	1	8	0	0
44113	1	3	0	0
44239	0	29	60	18
48005	1	3	4	10
48011	1	6	2	9
51423	1	1	0	1
51811	1	6	2	11
51817	1	0	0	1
51818	1	23	8	7
53411	1	7	6	4
62100	1	64	42	33
62110	1	1	1	1
62130	1	7	31	14
62140	1	17	39	24
66811	1	12	14	8
71511	0	57	19	21
71611	0	10	11	2
75227	1	0	1	0
76211	1	2	3	16
80111	1	0	2	0
81327	1	533	462	229
99785	1	27	40	0
99789	1	33	32	0

Note: Explanations to the codes of outcomes in www.vzp.cz