Estimating cost efficiency and determining the effect of specialization - A stochastic frontier approach on Finnish hospitals 2011-2013

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Abstract

This thesis estimated the cost efficiency and specialization of Finnish hospitals during 2011-2013 and determined how specialization affected hospital cost efficiency and what components of hospital output contributed most to hospital cost efficiency. A stochastic frontier model by Battese and Coelli (1995) with inefficiency effects was applied to a set of panel data to estimate the effect of exogenous variables on cost efficiency. The results indicate that Finnish hospitals are relatively cost efficient overall with a mean cost efficiency of 87% and have a relatively low degree of specialization. Specialization is associated with lower levels of cost efficiency. The results also suggest that university hospital status is not a significant determinant of cost efficiency in this sample. The findings contradict previous studies done on Finnish hospitals with regards to the effect of specialization on cost efficiency and as such prove a motivation for further research especially following recent studies done with new definitions of measuring hospital specialization with patient volumes instead of patient proportions. The findings are of current interest as Finland is in the midst of a health care system reform.

Denne oppgaven estimerte kostnadseffektiviteten og spesialiseringen av finske sykehus i 2011-2013 og analyserte hvordan spesialisering påvirket kostnadseffektiviteten til sykehus og hvilke komponenter i sykehusutgangen bidro mest til sykehuskostnadseffektivitet. En stokastisk frontier modell av Battese og Coelli (1995) med ineffektivitetseffekter ble anvendt på et paneldatasett for å estimere effekten av eksogene variabler på kostnadseffektivitet. Resultatene tyder på at finske sykehus er relativt kostnadseffektive samlet med en gjennomsnittlig kostnadseffektivitet på 87% og har en relativt lav grad av spesialisering. Spesialisering er knyttet til lavere nivåer av kostnadseffektivitet. Resultatene tyder også på at universitetssykehusstatus ikke er en viktig determinant for kostnadseffektiviteten for finske sykehus. Funnene er i motsetning til tidligere studier på finske sykehus med hensyn til effekten av spesialisering på kostnadseffektivitet og fungerer som motivasjon for videre forskning, særlig etter nylige studier gjort med nye definisjoner av sykehusspesialisering som måler spesialisering med pasientvolum i stedet for pasientproposjoner. Funnene er av nåværende interesse, da Finland er midt i en reform av helsevesenet.

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1 INTRODUCTION

The debate over privatization versus centralization in Finnish healthcare has been a hot topic for a long time – ever since the financial crisis hit in 2008 and the concern of an aging population and relatively too expensive of a public health care sector weighing on the minds of the public officials, the discussion over what direction to take the current health care system reform has flourished. The reform has been underway for more than 10 years now – with no consensus and final legal proposition achieved by any government.

Are specialized hospitals more efficient than large all-eggs-in-one-basket multifunction hospitals? More specifically, what is the relationship between cost efficiency of Finnish hospitals and their level of specialization?

These questions are central to the ongoing national health care system reform in Finland and this thesis aims to answer these questions in part and thus providing current useful information to the debate in process.

This thesis studied the cost efficiency of 48 Finnish hospitals over the years 2011-2013 and the effect specialization had on their cost efficiency. Following previous studies conducted by Linna (1998), Linna and Häkkinen (1999) and Lindlbauer and Schreyögg (2014), I applied stochastic frontier analysis on a unique, independently compiled dataset. The model for time-varying inefficiency developed by Battese and Coelli (1995) was utilized to estimate the cost efficiencies of Finnish hospitals in the sample and the effect specialization had. Stochastic frontier methods were chosen as the compiled dataset formed a panel and the effect of exogenous variables on inefficiency was of interest. The model choice and methodology are reviewed in detail and based on previous studies conducted on similar research questions.

I found that the level of specialization is associated with increased levels of inefficiency, in contrast to previous research done on Finnish hospitals. The mean level of cost efficiency were 87% in Finnish hospitals during 2011-2013, with a relatively low mean level of specialization of 0.66. The effect of specialization on cost efficiency was found to be negative. Some hospitals exhibited contrasting relationships between their specialization and cost efficiency levels and were presented in closer detail. The findings raise an interest for further research regarding the specialization level of Finnish hospital types and the definition of the specialization measure itself, as pointed out by Lindlbauer and Schreöygg (2014).

Thesis Structure

This thesis is structured in the following manner. Chapter 2 introduces the reader to the basics of hospital cost efficiency and specialization and introduces the research context. Chapter 3 presents the framework for the methodology utilized and defines the theoretical foundations of the model used in analysis. Chapter 4 reviews existing literature on this thesis's topic of research as a basis for the analytical choices made. Chapter 5 presents the model choice and the motivation behind it. Chapter 6 familiarizes the reader with the dataset used in analysis and defines the variables in more detail. Chapter 7 presents the analytical steps taken in model specification and the arguments behind model formulation. Estimation results are presented in chapter 8 for the frontier model, cost efficiency and the effect specialization has on cost efficiency. Chapter 9 concludes with a discussion.

2 HOSPITALS AS ORGANIZATIONS

This chapter introduces the reader to the theory and components of hospital cost efficiency, specialization and thus the context of this research topic in more detail. By the end the reader should have a basic understanding of what cost efficiency is, what the components are that a hospital's cost efficiency is composed of in terms of inputs and outputs and further how specialization is defined and measured.

2.1 COST EFFICIENCY

A hospital acts as an organization that produces an output with a given set of inputs that have a given set of prices.

The overall cost efficiency (CE) is the product of technical efficiency (TE) and allocative efficiency (AE). Intuitively, overall efficiency is the multiplied product of these efficiencies: CE = TE *AE.

The cost efficiency of a hospital can be measured if information on the prices of inputs is available.

Following Coelli et al.'s (2005) example: suppose **ω** represents the vector of input prices and **c** is the (observed) vector of inputs used in production, associated with point P in Figure 2.3.1. The figure illustration inspired by Farrell (1957) represents a situation where hospitals as organizations use two inputs, c_1 and c_2, to produce a single output, x, while exhibiting constant returns to scale.

Q depicts the technically efficient point of operations. I note the input vector associated with Q and the cost minimizing input vector at Q' as **c^** and **c***.

The allocative efficiency, or "price efficiency" as Farrell (1957) first named the term, and technical efficiency, can be calculated using the input price ratio. The input price ratio equals the slope of the isocost line, AA', in Figure 2.3.1. An isocost line represents all combinations of inputs that result in the same given cost. We can use the isocost line, AA', to measure TE, technical efficiency, and AE, allocative (price) efficiency.

(2.1.1) TE = $\frac{OQ}{OP} = \frac{\omega\prime\hat{}c}{\omega\prime c}$, 0≤TE≤1

(2.1.2) AE= = $\frac{OR}{OQ} = \frac{\omega\prime\hat{}c*}{\omega\prime\hat{}c}$, 0≤AE≤1

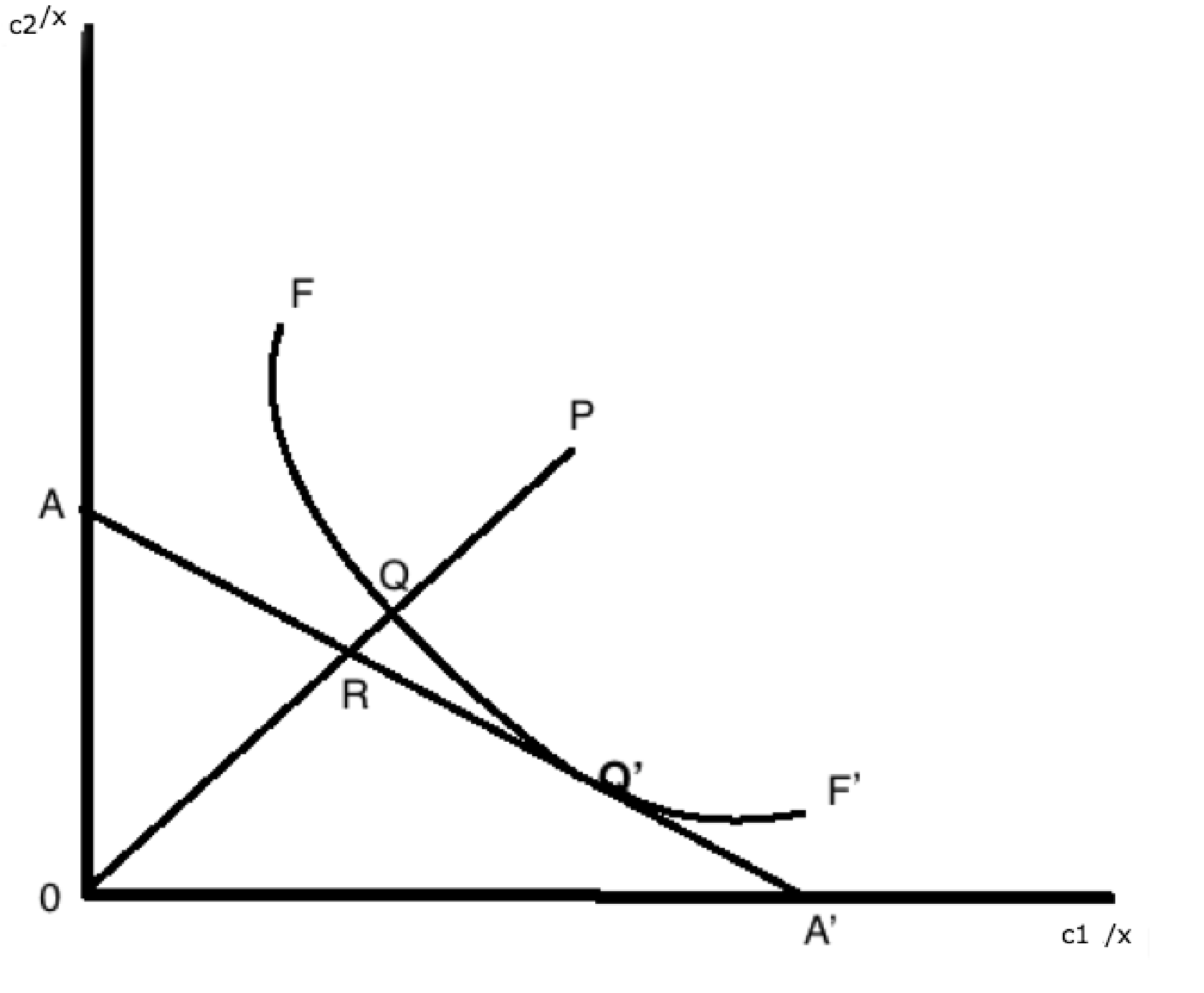

Figure 2.1.1: Operative optimums.

The intuition behind these equations follows from closer inspection of Figure 2.1.1. Point Q is the technically efficient, but allocatively inefficient operating point, whilst point Q' is the technically and allocatively efficient operating point. The distance RQ measures the inefficiency accumulating from the allocative (cost) inefficiency arising from operating at point Q instead of Q', which coincides with both the isocost line AA' and the production frontier FF'.

Cost efficiency (CE) can be calculated when the components, AE and TE, of this overall efficiency, CE, are known and as such, their relative position to the wholly efficient frontier.

(2.1.3) CE = TE * AE = (0Q/0P) * (0R/0Q) = (0R/0P), Following similar intuition as when measuring technical efficiency, the cost efficiency of a hospital is defined as the ratio of input costs associated with input vectors, **c** and **c*,** associated with points, P and Q' (Coelli et al. 2005). Such that

(2.1.4) CE = $\frac{\omega' c*}{\omega' c}$= OR / OP

The concept of cost efficiency and technical efficiency are closely related and for the purposes of this study, these concepts are necessary to define as allocative efficiency will be assumed and cost efficiency will be assumed to relate to technical efficiency later in this thesis.

2.2 COMPONENTS OF HOSPITAL EFFICIENCY

This section aims to give the reader a succinct understanding of the central components that create the framework in which a hospital's cost efficiency, and further, the effect of specialization, operate in when hospitals are treated as organizations. The following section will explain such definitions as Decision-Making Unit, inputs and outputs and how and why they are utilized in this thesis to study hospital cost efficiency and specialization.

2.2.1 DMUs

In efficiency analysis**, the focal point of analysis** is the organizational unit, the locus, of production – called the decision-making unit, DMU (Jacobs et al. 2006). The choice of DMU is an important part of the hospital cost efficiency analytical framework; the entire health system could be thought of as a DMU (World Health Organization 2000). Choosing the analytical unit defines the boundaries of the production process (Jacobs et al. 2006) – thus, the more clearly the unit's inputs and outputs can be defined and compared across different DMUs, the better.

Three criteria should be fulfilled regarding the DMU according to Jacobs et al. (2006):

1. A Decision Making Unit is defined as the boundary-setting unit of the analysis. This unit should capture the entire production process.
2. The definition of a DMU is that its function is to convert inputs into outputs by a discrete technological process by which the conversion takes place.
3. The units included in the analysis must be comparable by producing the same set of outputs.

This thesis studies 48 Finnish hospitals and thus has chosen to study the hospital level as its analytical level; one of the 48 hospitals is one DMU as all 48 DMUs are comparable across each other as all hospitals have clearly defined production processes and clearly defined inputs and outputs that are easily compared.

The inputs and outputs are defined and presented next.

2.2.2 Inputs

This section defines and categorizes health care inputs in theory and practice so that the reader understands the context in which they are utilized in this thesis.

Physical inputs can be usually summarized relatively easily as costs, or as a measure of costs. (Jacobs et al. 2006). Regarding efficiency analysis, the choice around inputs revolves around the level of disaggregation: a most aggregate measure of inputs can be used in the form of total costs, or, one can categorize inputs into subcategories, typically into labor inputs and capital inputs. These subcategories will be shortly presented below in order to give the reader an understanding of them as they are mentioned as explanatory factors later in this thesis. The choice of disaggregation level depends on the time horizon of the efficiency analysis – total costs may be used if a long-term analysis is of interest as the assumption that the hospital is optimizing its mix of labor and capital in its resultant total costs becomes valid over time. In short-term analysis, a more accurate knowledge over labor and capital inputs and a hospital's mix of these in their input use becomes more imperative. (Jacobs et al. 2006)

Labor

Labor inputs are typically categorized by skill level and weighted by wages. In this case as well, a long-term analysis that assumes market efficiency may benefit from an aggregated measure as it allows focus on other production processes that may contribute more to inefficiency. In short term analysis, the skill mix used regarding the labor force is of interest as it may yield inefficiency effects (Jacobs et al. 2006) .

Previous studies have utilized the wage rates of staff divided into occupational categories: physicians, nurses and other staff (Linna and Häkkinen 1999) or the number of personnel divided into occupational categories as listed (Lindlbauer and Schreyögg 2014).

Capital

Capital inputs are rather difficult to accurately measure and are often due to difficulties in accurate measures of capital stock or additional inaccuracies encountered when assigning use of capital stock to specific time periods. As with labor inputs, a more concise breakdown is necessary in short-term analysis of efficiency and more aggregate measures may suffice the longer the time horizon is in the analysis (Jacobs et al. 2006). Previous studies have used such proxies for capital as number of beds (Lindlbauer and Schreyögg 2014) and total capital expenditure divided by number of available hospital beds (Farsi and Filippini 2008).

This thesis utilizes an aggregated measure of inputs and thus utilizes total operating costs per annum as inputs. The motivation for this choice is such that as explained above, in a cross-sectional study, a more disaggregated level of measurement regarding inputs would be desirable but as this thesis utilizes panel data this becomes less imperative (Jacobs et al. 2006). In addition, there was a lack of comprehensive and available data on capital inputs. Capital and labor inputs were regarded as zero-sum addition as the factor prices are set through a central bargaining process in Finland and as such, their effect on the operating costs can be considered equal to 1 and the prices are considered exogenous in this study. Thus, the aggregation level was set to total operating costs for inputs.

2.2.3 Outputs

This section aims to shed light to the definition of health care outputs in theory and practice. As operating costs are utilized as input variable in this study, outputs must be defined as they act as the counterpart and directly contribute to the magnitude of the total costs in addition to inefficiency effects. The output measure utilized in this thesis is the Diagnostic-Related Group –adjusted output and the next sections will explain these concepts in more detail.

The most accurate measure of health care outputs should revolve around health care outcomes, according to Jacobs et al. (2006) - inputs in general are relatively easier to define and measure in a more accurate fashion than outputs in health care organizational efficiency analysis. Demand for health care is derived from the underlying demand for the benefits gained from an increase in health status; ability to worker more wage-paying hours, for example. (Grossman 1972). Interpreting this, health care outputs should be defined as ***outcomes of health care,*** as in, value-added health care**.** (Jacobs et al. 2006). This poses a problem at defining health care outputs since mostly all hospitals and other health care organizations gather only quantity-based data on treated patients, whilst studying change in health outcomes requires quality-based data.

As a solution to lack of quality-of-care-based data on patients' health outcomes, previous research has focused on defining health care outputs as ***health activities***.

Health care activities are either variables such as patients treated by a hospital, operations undertaken or outpatients seen (Jacobs et al. 2006). These measures of activities are oftentimes used as proxies for outcome as a necessity. Previous studies have utilized such proxies as mortality rates or readmission rates (Linna and Häkkinen 1999). A problematic feature of these proxies is the fact that they disregard taking into account the quality-based change in output, that is, the change in health status as a result of the hospital's activity. (Jacobs et al. 2006)

Modern efficiency research has mostly solved this issue by creating Diagnostic-Related Groups (DRGs) and utilizing DRGs as a measure of outputs. DRGs take into account a standardized activity measure in quantity that also includes a quality measure by determining the final product of hospital care. Linna and Häkkinen (1999) note that the DRG system suffers from some bias as it does not fully take into account the severity of patient illness, quoting both Horn et al. (1986) and Averill et al. (1992). However, as the DRG system is used as an aggregated measure into a single output ”the effect of this bias remains unclear” (Linna and Häkkinen 1999).

The outputs measured are divided into desired output categories and then adjusted for that category's DRG-use, such that each output is corrected for its resource-intensity and severity, thus making them more comparable.

DRG-adjusted outputs are utilized in most studies conducted and thus, in this thesis as well. As this thesis chooses to use a singular aggregated measure for inputs, a single aggregated measure for outputs is a straightforward choice for the other side of the equation. The output categories this thesis uses in its study are: day surgery, emergency services, outpatient services, inpatient services and procedural services.

A more concise description on the output variables used can be found in chapter 6 called 'Data'.

2.2.4 Diagnosis-Related Groups (DRGs)

This section aims to explain what Diagnosis-Related Groups (DRGs) are and how they are used in the context of hospital cost efficiency analysis. This thesis utilizes DRGs in its output measures as the outputs are adjusted to account for intensity and severity of resource use in each patient treatment category.

”The motivation behind using DRGs was to simplify the hospital product definitions, in order to assess hospital performance, develop hospital operating processes, monitor the quality of care and develop performance-based budgets. At national level, DRGs are used for hospital benchmarking”, Kautiainen et al. (2011) summarize.

Nowadays benchmarking data is routinely collected from Finnish hospitals and available at The National Institute for Health and Welfare’s (THL) website for the public.

This efficiency analysis utilizes this specific benchmarking data as well.

DRG systems were created when the necessity of hospital systems that take into account patient variety and the intensity of resource usage became apparent. Dr. Eugene Codman spoke to the Philadelphia County Medical Society already in 1913 that “We must formulate some method of hospital report showing as nearly as possible what are the results of the treatment obtained at different institutions. This report must be made out and published by each hospital in a uniform manner, so that comparison will be possible. With such a report as a starting-point, those interested can begin to ask questions as to management and efficiency”. (Wiley 2011)

Classification of patients into DRGs is done based on the critical classification variables: diagnoses and procedures. This makes it critically important that hospitals use a standardized coding system to sort their patients under coded diagnoses and procedures such that universal DRGs can eventually be created. The Nordic countries utilize a coordinated NordDRG system in which both Finland and Sweden as most countries, for example, use only a slightly modified version of the WHO ICD-10 (10th revision of the International Classification of Diseases) coding standard for diagnoses and Iceland and Denmark, for example, use NCSP (Nordic Medico-Statistical Committee Classification of Surgical Procedures) for procedures. (Linna and Virtanen 2011)

As patients are classified into DRG groups, each DRG group is then allocated a weight based on the severity and intensity on the resource-use (that is, the average cost of inputs) their particular DRG group, on average, uses up in during an in-patient episode of treatment in order to achieve a satisfactory health outcome. This weight is known by definition as the casemix index (CMI) of that Diagnostic Related Group.

To summarize, as the patient's medical information is stored in a standardized format and all medically similar patients are grouped into diagnostic and procedural categories, universal resource usage on average for such a patient is calculated across all hospitals. Thus it is known how resource-intensive it typically is to treat such a patient into health on average, and thus, hospitals can be compared across the board on their cost efficiency. This system is depicted in the figure 2.2.4.1 below.

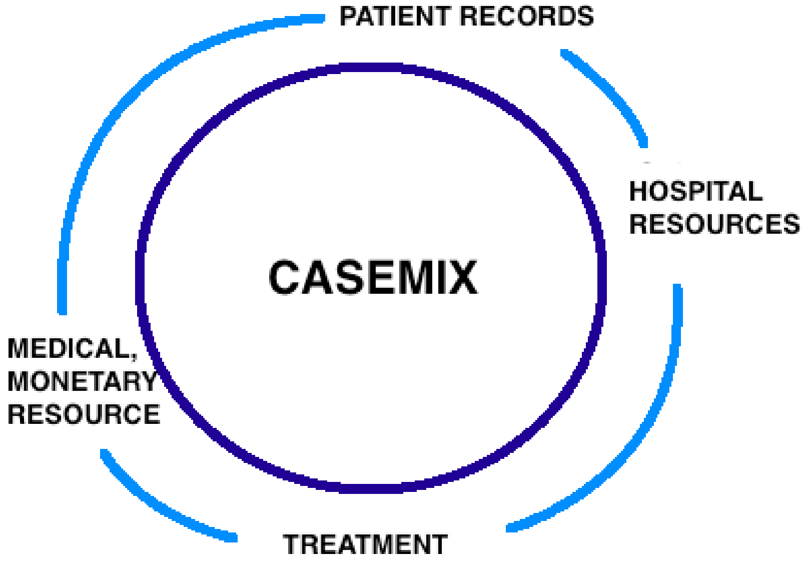

Figure 2.2.4.1: The components of casemix.

The specifics of the categorization of patients into diagnosis and procedures categories (a mix of cases, ie. cohorts) depend on a case-mix specialization system. Additionally, the degrees at which patients are concentrated to certain DRGs within a hospital affect that hospital's overall variety of patient mix.

This specialization system with the degree of concentration of patient variety together contributes to the other central focus of interest of this thesis – the degree of specialization of a hospital. As cost efficiency depends not only on how resource-intensively a hospital treats its patients – but also on how specialized the variety of patients the hospital treats and thus how specialized the hospital is its resource-intensity.

The specifics of hospital specialization are presented next.

2.3 SPECIALIZATION

Specialization is measured with an Information Theory Index (ITI). This section will define this concept for the reader so that the reader will have an understanding of why hospital specialization is of interest when estimating hospital cost efficiency and how hospital specialization is measured.

In order to compare efficiency between hospitals, one must take into account the variety of patient cases that are treated between hospitals – the heterogeneity. This variety includes the severity of illness and variety of diagnoses a hospital treats, according to the DRG system presented in the previous section. A small, highly specialized hospital can be assumed to use less input resources (both capital and labor) to produce a satisfactory treatment outcome, especially for a less severe diagnosis and procedure category, than for example, a large university hospital, with several specialties and a highly heterogeneous patient mix.

The Information Theory Index (ITI) was originally applied to economic research as a tool to quantify information gains by Theil (1967, 1971).

Additionally it has been utilized as a measure of hospital specialization as it quantifies how concentrated a hospital's knowledge in certain specializations (or patient categories) are. Basic economic theory may (Smith 1776) suggest that specialization may lead to advantageous resource usage due to, for example, knowledge advantage, skill advantage, economies of scale within the specialty and additional competitive advantages.

If hospitals treat very dissimilar patient mix profiles over time and thus become accustomed to treating a very specialized or a very generalized patient mix, yet this patient mix is not taken into account when these hospitals are compared in their cost efficiencies, the results may be inaccurate.

Farley (1989) applied ITI to hospital discharge data following Evans and Walker's (1972) first application of ITI to hospital casemix data.

Mathematically ITI compares two distributions. ITI measures hospital's share of medical diagnostic categories compared to national (or a sample's) averages weighted by shares of patients in each category (Kobel and Theurl 2013).

The mathematical formulation of ITI is as follows

(3.x.x) $ITI_h = \sum_{i=1}^{N} p_{ih} \ln(\frac{pih}{\Delta i})$

where

ITI represents the Information Theory Index of hospital h and it measures the sum of logged differences for all categories of hospital h compared to the average (usually the national average), weighted by the share of patients in each category i.

p_{ih} represents the share of DRG patients in category i relative to all DRG patients treated at hospital h while Δ_i measures the (national) average share of DRG patients in category i relative to all DRG patients being treated. Thus ITI_h is a measure of the degree of a hospital's specialization in the DRGs.

ITI_h is equal to 0 if no specialization occurs and the hospital DRG patient proportions are equal to national shares, ITI_h increases with the level of specialization (Linna and Häkkinen 1999).

The degree of specialization of Finnish hospitals and their specialization profiles are discussed in more details in the 'Analysis' and 'Discussion' -sections of this thesis.

3 OVERVIEW OF METHODOLOGY

”In contrast to DEA, the stochastic frontier approach captures random fluctuations which has often been viewed advantageous when analyzing cost efficiency.” – Li and Rosenman 2001

The following section will familiarize the reader with the empirical methodology applied in this thesis and further derive the stochastic frontier models considered and utilized. This section will derive the development of stochastic frontiers, the distributions of the error term and their effect on empirical estimations. A reference to DMU in the section holds true to any hospital as well – the choice to refer to a DMU is due to the following material being applicable to other sorts of DMUs in addition to hospitals as well.

3. 1 STOCHASTIC FRONTIERS

Stochastic frontier analysis (shortened as SFA from here on) was developed separately and independently from each other by Aigner et al. (1977) and Meeusen & van Den Broeck (1977). SFA relies heavily on the production or cost function of the DMU and especially on the utilization of the production or cost function in the process of analytics of the data. SFA’s purpose is to determine the parameters of the production or cost function.

Before Aigner, et al. (1977) and Meeusen & van Den Broeck (1977) simultaneously published their work on stochastic frontier analysis, the pre-existing research was known as deterministic frontier analysis. Stochastic frontier analysis refers specifically to the stochastic noise found in the error term in the parametric cost (or production) function, as in, the stochastic noise represents the inefficiency by which the DMU is deviating from the efficient frontier – an efficient producer would have no stochastic noise in their cost (or production) function.

The road approaching SFA came into fruition in the form of Corrected Ordinary Least Squares (COLS), which utilized the familiar Ordinary Least Squared (OLS) methodology. The method relies quite simply on first estimating the frontier by OLS and then *correcting* the frontier to correctly fit the observed data. The two applications of OLS to efficiency frontier estimation are known as

COLS and Modified OLS (MOLS) – the former was developed by Winsten (1957) and I will only focus on and present the COLS model due to COLS being more relevant to the development of SFA and later panel data applications of SFA.

Say, a DMU operates according to a cost function such as

(3.1.1) $C = f(X,w,r)$

Where C refers to the DMU's total costs

X refers to the DMU's total output

w refers to the input price of labor (wages)

r refers to the input price of capital (rent)

And this cost function takes a common Cobb-Douglas form of

(3.1.2) $C(X,w,r) = \alpha(Xw^{\beta}r^{\gamma})^{1/(\beta+\Upsilon)}$

And thus the linear form of the cost function can be written and estimated as the total costs of DMU i are

(3.1.3) $\ln C_i = \alpha + \frac{1}{\beta+\Upsilon} \ln X_i + \frac{\beta}{\beta+\Upsilon} \ln w_i + \frac{\Upsilon}{\beta+\Upsilon} \ln r_i + \varepsilon_i$

In which the residual ε_i is especially of interest and where α, β and Υ the Cobb-Douglas parameters to be estimated.

First, (3.1.3) is estimated by regular OLS. Once this estimation is done, the residuals would be utilized to shift the frontier to fully envelope the data and correct to fit the frontier. As Jacobs et al. (2006) note, residuals are not awarded special attention in usual regression analysis – however, Farrell (1957) suggested they can be used to quantify inefficiencies. Specifically, the residual itself can be used to describe to which extent a DMU operates from best practice. In the case of this cost function, if the residual is estimated at zero the DMU operates at average efficiency, but if it is estimated at negative values the DMU is operating above average efficiency.

Thus, the residual's magnitude represents its efficiency in a quantifiable manner and is comparable to other DMUs in the sample. The DMU with the 'most-negative' residual value is considered to operate with the least-cost practice and is thus most efficient at cost-minimizing. This observation is thus considered to be lying on the frontier of the sample. (Jacobs et al. 2006)

Regarding COLS, the cost function frontier can then be estimated by adding min (ε_i) to the intercept α and subtracting it from the residuals – this procedure is known as the corrected ordinary least squares method.

As OLS creates a regression line that falls through the centre of observed data, COLS grabs the regression line and shifts it so that it passes through the observation displaying minimum cost (Jacobs et al. 2006).

The residuals for COLS defined as $\varepsilon_{min} = \min(\varepsilon_i)$ as before and thus the intercept can be written as:

(3.1.4) $\alpha_{COLS} = \alpha + \varepsilon_{min}$

A graphical illustration of the manner in which the COLS approach grabs the OLS regression line to fit the best-practice (minimum-cost) observation to fit the regression line through it through the cloud of observed data below.

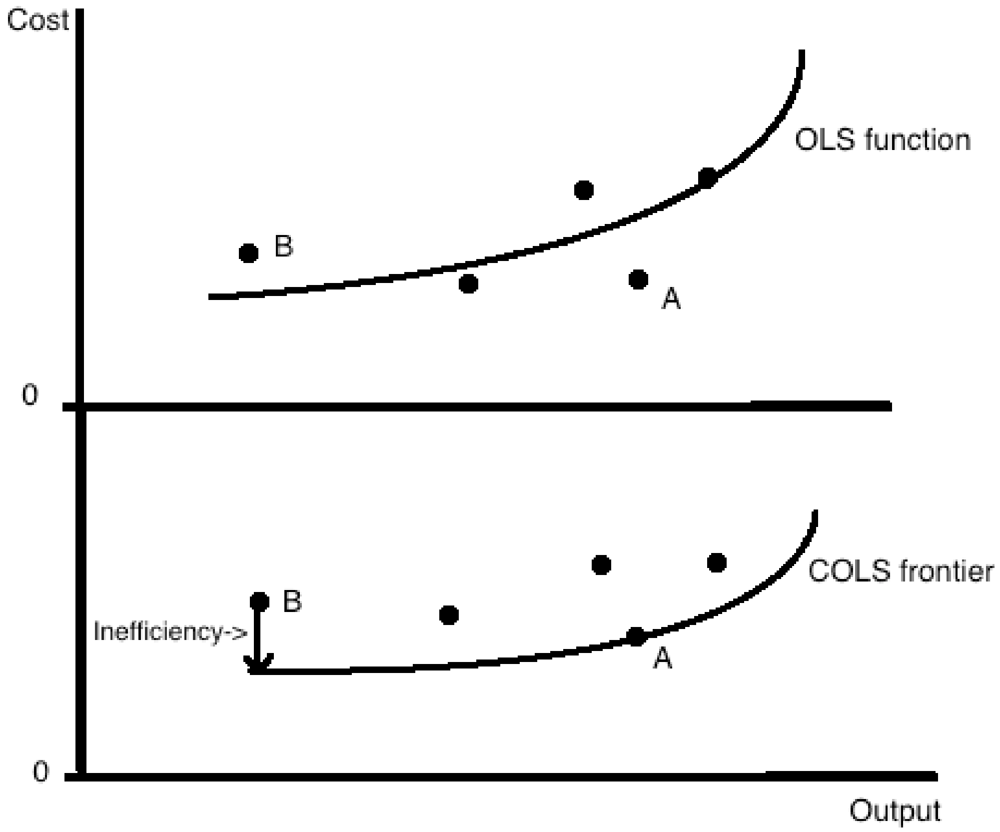

Figure 3.1.1: COLS vs. OLS (recreated from Jacobs et al. 2006)

Point A illustrates the minimum-cost observation, which also acts as the cost efficient frontier. The COLS frontier illustrations shows the shift to down so that the regression (frontier) line can cut through point A. Inefficiency can be measured as the distance between points and the frontier.

COLS has a few setbacks though and the major one is the assumption that the magnitude of the residual is all due to inefficiency. This assumption was critized for being too simplifying and led to the development of stochastic frontier analysis – as SFA was developed on the basis that the residual was composed of two components: inefficiency and random (stochastic) error.

SFA can econometrically estimate the inefficiency component and the stochastic error component separately. The essential assumption regarding the residual and its components is that the random term is normally distributed (thus is consistent with the OLS model). Wagstaff (1989) noted that if the residual ε_i is normally distributed then all variance in the residual term is thought to be caused by random noise and measurement error. Schmidt and Lin (1984) had already brought along the notion that if ε_i is not normally distributed then it is proof there exists inefficiency.

SFA then decomposes the residual term into two components. Following Aigner et al. (1977) a cost function error term for DMU i can be decomposed into two parts with zero covariance such that

(3.1.5) $\varepsilon_i = v_i + u_i$, $\mathrm{cov}(v_i, u_i)=0$

where v_i represents the random stochastic component of the variance. According to Aigner et al. (1977) these can be environmental shocks and thus resulting in random events and random noise in the residual. v_i captures such effects that are not controlled by the DMU itself but that have an effect on the DMU's costs. v_i may also reflect measurement error for example.

u_i can be interpreted as the non-negative, DMU-specific deterministic inefficiency component separately from the stochastic random term as v_i and u_i are independently distributed from each other (and the regressors). u_i reflects the distance by how far the DMU lies from the efficient frontier and directly measures the inefficiency of the DMU in question.

3.2 THE DISTRIBUTION OF THE ERROR TERM

Regarding estimation of the random term and the inefficiency term, defining their distributions is essential – specifically when estimating cross-sectional data. When utilizing cross-sectional data, thus only observing DMUs at one point in time, it is essential to determine how inefficiency, u_i, is distributed among the organizations in the sample.

As this thesis is studying a sample of panel data, defining the distribution of the inefficiency term is not of such critical importance but it does highlight the advantage of working with panel data as it diminishes the possible problematic issues arising with distributional assumptions.

The several distributional alternatives are derived in this following section so that the reader will have an understanding of how the inefficiency term is determined and further how the inefficiency term behaves in the stochastic frontier model applied to the data in this thesis.

The random error term, v_i, is assumed to be normally distributed with a zero mean and constant variance following Aigner et al. (1977):

$v_i \sim N(0, \sigma_v^2)$

The distribution of the inefficiency term, u_i, is not predetermined as noted by Schmidt and Sickles (1984). Greene (1990) lists the four options to choose from as distributional choices for u_i as: the half-normal distribution, truncated normal, exponential and the gamma distribution.

In a nutshell, the central element of SFA is choice of distribution of the inefficiency term so that the mean of inefficiency lies relatively close to zero in a manner that DMUs distributionally mostly operate in the efficient range (Hokkanen 2014; Coelli et al. 2005).

The half-normal distribution is defined by

$u_i \sim N^+(0, \sigma_u^2)$

where $N^+(\ )$ refers to a half-normal distribution (Aigner et al. 1977).

u_i must be observed indirectly since the components of ε_i cannot be directly estimated, only ε_i can be (Jacobs et al. 2006).

This procedure consists of defining the expected value of u_i conditional on upon ε_i.

Following Jondrow et al. (1982), the expected mean value of u_i under the half-normal distribution can be written as

(3.2.1) $E[u_i|\varepsilon_i] = \frac{\sigma\lambda}{(1+\lambda^2)} [\frac{\phi(\varepsilon i\lambda/\sigma)}{\Phi(-\frac{\varepsilon i\lambda}{\sigma})} - \frac{\varepsilon i\lambda}{\sigma}]$

where $\sigma^2=\sigma_u^2 + \sigma_v^2$; $\lambda=\sigma_u/\sigma_v$ reflect inefficiency.

$\phi(\bullet)$ is the probability density function while $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution.

Greene (1993) showed that when $\lambda=\sigma$, every observation in the sample lies on the efficient frontier.

The truncated normal is a more general version of the half-normal model and thus the half-normal can be expanded to present the normal model. Stevenson (1980) showed that the conditional expectation of mean of the normal form of the distribution where $\frac{\varepsilon i\lambda}{\sigma}$ is replaced by

$u_i{*}= \frac{\varepsilon i\lambda}{\sigma} + \frac{\mu}{\sigma\lambda}$

where u is distributed with the modal value of μ.

If $\mu \cong 0$, the expanded normal model collapses into the half-normal model.

A large variety of models estimating technical and cost efficiency utilize the Jondrow et al. (1982) estimator of the conditional expected mean of u_i.

Meeusen and van Den Broeck (1977) similarly derived the exponential distribution for the inefficiency term to be written as

$u_i \sim \exp(\theta)$, such that $\sigma_u = \frac{1}{\theta}$

Both the truncated normal and the exponential distributional assumptions carry with them the assumption of non-negative mean of inefficiency values, binding the value range minimum at zero and maximum efficiency (as in, the frontier) at a value of one. Some researchers choose to avoid utilizing these distributional choices due to the non-negativity assumption (Coelli et al. 2005).

Following Greene (1995) the exponential distribution leads to expected u_i, conditional on the residual, being written as

(3.2.2) $E[u_i|\varepsilon_i] = (\varepsilon_i - \theta\sigma_v^2) + \frac{\sigma v\phi}{\Phi} [\frac{(\varepsilon i-\theta\sigma v2)/\sigma v)}{(\varepsilon i-\theta\sigma v2)/\sigma v}]$

in which θ is the parameter to be estimated.

In this exponential case, the density function takes the more general form

$g(u_i)= \theta exp^{-\theta ui}$

From which the more general gamma distributional case can be expanded according to Greene (1990) in a fashion that an extra parameter D is added to the density function g so that

$g^g(u_i)=\frac{\theta^D}{\Gamma(D)} u^{D-1} exp^{-\theta ui}$

with $u_i \sim G[\theta,D]$

Regardless of the distributional choice, the estimator of u_i might not be skewed but it will be inconsistent (Greene, 1993).

No solution has been found to fix this particular issue regarding the inconsistency of the estimation of the inefficiency term, u_i, in cross-sectional data, but some of the pitfalls can be avoided when DMUs are observed over several points in time as in panel data as this thesis does and was one of the reasons a stochastic frontier model was deemed suitable for this particular analysis.

The choice of panel data model and its specific error term components are derived in the following sections.

SFA models for panel data are derived in the next section.

3.3 SFA AND PANEL DATA

As discussed in the previous section with cross-sectional data, the difficulties that arise with estimation of the inefficiency term revolve around the strong assumptions that must be made about the residual and its components' distributional properties. With panel data, I can relax some of these strong assumptions or undergo them completely, estimate the DMU-specific inefficiencies consistently and allow correlation between inputs and the inefficiency term u_i - although in many cases the number of observations is not high enough for all of these three conditions to be completely fulfilled (Kumbhakar and Lovell 2000).

A difficulty arising with panel data specifically is unobserved heterogeneity that must be controlled for unless it may lead to biased estimates of frontier parameters and overestimates of inefficiency u (Kumbhakar et al. 2015). Heterogeneity between hospitals, for example, is a major factor causing individual variation in their operating costs with seemingly no observable direct input and while classified as a difficulty, this heterogeneity is also a tool that can be used as a beneficial tool in analysis. Baltagi (2005) describes controlling for it as a "key benefit" of panel data.

Individual heterogeneous factors affecting their costs are such as environmental factors (location, size) whose effects are only partially observed.

A solution to control for the heterogeneity is to apply a time-invariant model to the data so that the inefficiency term is DMU-specific (Castiglione et al. 2017).

3.3.1 TIME-INVARIANT MODELS

Time-invariant inefficiency effects can be estimated by either fixed (by ordinary least squares) or random effects models (by maximum likelihood or generalized least squares).

The fixed effects (FE) model requires no assumptions to be made about the distribution of the error term or whether or not inefficiency is correlated with the regressors. However, the fixed effects model is oftentimes suffering from certain limitations in practice; FE models may capture excluded time-invariant effects and wrongly attribute this to the inefficiency term (Greene 2005) and if there is measurement error in the explanatory variables the coefficients may tend towards zero causing results to falsely indicate as having little to no effect (McKinnish 2000). Specifically, if one wishes to include time-invariant regressors in their cost function that is to be estimated, fixed effects cannot be included as the intercept will capture any DMU-specific time-invariant effects.

The major issue with such time-invariant models and choosing to apply them to this thesis's data is the fact that they require a) a two-stage estimation which generates biased estimates if one wishes to estimate the effect specialization has on cost efficiency since there is no way to include exogenous factors into the frontier model and b) even if the models did allow for exogenous factors, fixed effects models do not allow the inclusion of time-invariant variables such as proxies for hospital size which this thesis may wish to control for, as it may be a relevant factor as the literature review later on discusses.

Both of these points are addressed concisely in the section devoted to Model selection in chapter 5.

Alas, Battese and Coelli developed a time-varying random effects model in 1995 that allowed a one-stage estimation with the inclusion of exogenous variables. This model will be derived next.

3.3.2 TIME-VARYING MODEL

3.3.2.1 BATTESE AND COELLI 1995

In 1995, Battese and Coelli (1995) further developed a time-varying inefficiency model into a one-stage model that included independent variables explaining the inefficiency term being estimated simultaneously with the frontier, eliminating any possible bias in the estimates the previously mentioned two-step process may have been creating.

It is not always a valid assumption to impose on hospitals that their efficiency has been constant over time and in contrast to the time-invariant fixed and random effects models in the previous section, I'll allow inefficiency to vary over time in this section.

Heterogeneity is allowed and utilized within the inefficiency term.

A simple approach to time-varying efficiency is to assume the temporal change is the same for all hospitals in the sample.

The framework of the Battese and Coelli (1995) model adapted to a cost frontier can be written as

$$\text{(3.3.2.1.a)}\ \ln C_{it} = \alpha + \beta x_{it} + u_{it} + v_{it}$$

where

$\ln C_{it}$ are the natural logarithm of total operating costs of hospital i at year t, t=1,..,T

α is the constant intercept, giving the value of ln C of hospital i at year t if all other variables are at 0

x_{it} are a vector of output variables associated with hospital i at year t

β are a vector of unknown parameters to be estimated

$v_{it} \sim N(0,\sigma^2_v)$ are random errors independently distributed of u_i's

u_{it} are non-negative random variables associated with cost inefficiency, are independently distributed and obtained by truncation of the normal distribution such that

$u_{it} \sim N(z_{it}\delta,\sigma^2_u)$ has a mean of $z_{it}\delta$, where z_{it} is a vector of independent explanatory variables associated with cost inefficiency of hospital output over time t and δ is a vector of coefficients.

In this thesis, the primary variable we set into the place of z_{it} is the degree of specialization, ITI.

A Battese and Coelli (1995) summarize, if all the δ's equal 0, the inefficiency effects are unrelated to the explanatory variables and a half-normal distribution is exhibited (specified originally by Aigner et al. (1977)), whilst the case of the first z-variable having a value of 1, then the half-normal case become generalized to the normal-model defined by Stevenson (1980). Both of these distributions are defined in detail in the previous section under 3.2. In short, the inefficiency effects are assumed to be positive and the half-normal distribution is a special case of the truncated normal case.

The cost inefficiency effects can be specified in a secondary function so that

$$(3.3.2.1.b)\ u_{it} = z_{it}\delta + V_{it}$$

where V_{it} is a random term with a truncated normal distribution, zero mean and variance σ^2.

u_{it} and v_{it} are assumed to be independently distributed.

Allocative efficiency is assumed so that u_{it} relates to the cost of technical inefficiency (Coelli 1996).

Simultaneous estimation of 3.3.2.1.a and 3.3.2.1.b is proposed by Battese and Coelli (1995) by Maximum Likelihood Estimation (MLE) to get the parameters of the stochastic frontier and the inefficiency model so that the parameters **β** are estimated.

Additional parameters to be estimated by MLE are expressed in terms of the variance functions are

$$(3.3.2.2)\ \gamma \equiv \sigma^2_u / (\sigma_v^2 + \sigma_u^2)$$

$$(3.3.2.3)\ \sigma^2 = \sigma_v^2 + \sigma_u^2$$

and γ variance ratio depicts how much of the error in the sample is caused by inefficiency relative to random noise and thus how meaningful the inefficiency effects are in the model. γ receives a value between 0 and 1 with zero depicting no inefficiency contributions to the variance found in the sample and one depicting all of it. This ratio is further stripped down in empirical estimations to a straightforward ratio of standard deviations, originally depicted by Aigner et al. (1977)

$$(3.3.2.4)\ \lambda = \hat{\sigma}_u / \hat{\sigma}_v,\ \lambda \geq 0$$

in the estimation results later in which any positive values are depicting inefficiency effects found.

Efficiency is calculated in the following manner for cost functions with logged left-hand-side variables, as depicted in Table 3.3.2.1.1 below.

Function type	Logged dependent variable?	Efficiency
Cost	Yes	$\exp(u_{it})$

Table 3.3.2.1.1: How to calculate efficiency (from Coelli 1996)

Cost efficiency (CE) is thus (Coelli 1996, Battese and Coelli (1995) production function modified):

$$(3.3.2.5)\ CE_{it} = E((C_{it}^*) \mid u_t, x_{it})/E((C_{it}^*) \mid u_{it}=0, x_{it}) = \exp(u_{it}) = \exp(z_{it}\delta + V_{it})$$

Where C^*_{it} is the value of C of the i^{th} hospital and it equals exp (C_{it}) in case the variable is in log-form.

For cost functions, the values of CE_{it} will fall between 1 and infinity, so taking the inverse of CE_{it} is advisable such that $0 < \frac{1}{effi} < 1$. The above expression for CE_{it} is the predicted, expected value of u_{it} conditional on the observed value of the residual ($u_{it} + v_{it}$).

Untransformed (numeric) variables will yield efficiency estimates that represent absolute distances from the frontier while logarithmic variables yield percentage distance estimates from the frontier (Jacobs et al. 2006). In this study the results obtained will therefore be interpretable in percentage distances from the frontier.

4 LITERATURE REVIEW

This section aims to review the existing literature that most closely relates to the topic of this thesis, hospital cost efficiency and specialization, and the methodology most often utilized in current literature with similar data to study the research question of this thesis. By the end the reader should have an overview of how hospital cost efficiency and specialization have previously been studied, and the models that have been used. In addition, the reader should be ore aware of the factors that are empirically important to take into account when studying this research question and furthermore the reader shall understand the motivation behind choosing SFA and the model in this thesis and also why specialization is a factor of interest when studying hospital cost efficiency.

As stochastic frontier analysis is a relatively modern empirical method of analysis, only having been developed in 1977 by Aigner et al.(1977) and Meeusen and van Den Broeck (1977) simultaneously, the utilization of SFA in efficiency analysis pales in comparison to its counterpart Data Envelopment Theory (DEA) originated by Farrell (1957). DEA differs from SFA essentially by lacking economic framework and instead molds the frontier to the data – quite the opposite as to how SFA operates. For a long time, DEA dominated the field simply by being simpler to work with - however even in healthcare efficiency analysis, SFA has emerged as a valid alternative to DEA especially as it fulfills the desire for a sound economic theory as pedestal that the analysis can be built upon.

Hospital efficiency has been studied as other industries and their efficiencies much in the same manner by DEA until Wagstaff (1989) first applied stochastic frontier analysis to estimate the efficiency of 49 Spanish hospitals. Since his study, a wide range of research has been conducted to study hospital efficiency with SFA.

A noteworthy trend in previous studies has been the lack of panel data – the majority of research has utilized cross-sectional data and thus the majority of previous studies have most likely conducted data envelopment analysis as SFA requires somewhat restricting empirical assumptions that can be lifted if panel data is available.

Hollingsworth (2003) reviewed 188 studies on non-parametric and parametric applications that measured efficiency in health care, of which 50% utilized DEA methodology to estimate efficiency and only 12% applied SFA or similar frontier studies. Two thirds of the published papers has conducted their study on data from US organizations (hospitals and nursing homes) which makes direct comparisons difficult to European and especially Nordic studies but as this literary review shows, the contrasting results from efficiency studies provides a board for discussion as to find the determinants of the opposing results.

As noted in section 2.2 of this thesis, the more encompassing measure of health care output should be health outcome that takes into account the quality of health care directly (Jacobs et al. 2006) but only ten of the papers reviewed utilized health outcome changes as output variables as opposed to measures of physical activity such as inpatient days (Hollingsworth 2003). Input variables are in large part measures of employees (labor) or capital.

The overall comparison of inefficiency results of SFA studies on hospital performances show a wide variety of inefficiency scores; Wagstaff's (1989) study found 28% inefficiency in Spanish hospitals while Linna and Häkkinen (1999) found efficiency scores of Finnish hospitals to lie between 0.86 and 0.93. Wagstaff and López (1996) studied the efficiency of 43 Catalan hospitals and found inefficiency to lie at 58%. Li and Rosenman (2001) found average inefficiency of Washington state hospitals to be around 33%. The range of efficiencies is clearly wide.

Eastaugh (1992) studied the relationship between hospital cost efficiency and specialization, utilizating panel data and multiple regression analysis. The standard for the field were already taking place as the study utilized an Information Theory Index (ITI) measure for specialization and DRG-adjusted output variables. The same standardized measures are still in use in today's research. Eastaugh (1992) found that specialization was associated with lower unit costs and increased quality and that most specialized hospitals were found in the most competitive markets.

M. Linna has conducted a notable share of the study of the performance of Finnish hospitals. Linna and Häkkinen (1995) studied the cost efficiency of 46 Finnish hospitals via SFA, Linna et al. (1998) utilized SFA to study the costs of teaching and research in Finnish hospitals and found that university hospitals across board were more efficient in both regards, Linna and Häkkinen (1999) compared DEA and SFA in estimation of the determinants of cost efficiency of Finnish hospitals and found that specialization (ITI) and specialization in expensive Diagnostic Related Groups contributed to efficiency and Linna (1998) found in his panel data study on Finnish hospital cost efficiency that approximately half of the productivity increase was due to improvement in cost efficiency and half due to technological change.

Following Linna's work, similar studies have been conducted mainly on US hospitals. Comparisons, naturally, are difficult to draw directly since the healthcare systems between the Nordic countries and USA are rather different but methodology and the application of SFA has followed a similar path. Li and Rosenman (2001) estimated the cost efficiency of Washington state hospitals using panel data and utilizing SFA and found that larger hospitals were less efficient relative to smaller hospitals. They didn't have DRG-adjusted output variables so they used a casemix-index to control for patient variety between hospitals. Their findings interestingly contradict for example Linna's typical findings of Finnish hospitals.

Rosko (2004) estimated the performance of US teaching hospitals with a panel data study on cost efficiency and utilized the one-step model for estimating panel data efficiency by Battese and Coelli (1995). Rosko (2004) found that US teaching hospitals increased their efficiency as a result of external fiscal pressures; fiscal pressures were used as the exogenous variable in the one-step model that estimated cost efficiency and how fiscal pressures affected it.

Farsi and Filippini (2008) studied the cost efficiency of Swiss hospitals and applied SFA on panel data. They studied the effect of several exogenous variables on the cost efficiency of hospitals and found that in the case of Swiss hospitals, teaching activity was a significant driver for inefficiency and that university hospitals were less efficient. Thus Farsi and Filippini's (2008) results from Swiss hospitals mirror those of Li and Rosenman's (2001) from USA – whilst Finnish teaching university hospitals contrast these findings according to Linna et al. (1998). Farsi and Filippini (2008) also found that there were present unexploited economies of scale in most hospitals –a logical finding as university hospital status and number of beds were correlated with higher costs.

As hospital cost efficiency has been studied quite extensively in a variety of manner ever since the inception of DEA and furthermore since the development of SFA, existing research on hospital cost efficiency related to specialization is a relatively seldom-studied topic. A relevant study on this very topic was conducted by Lindlbauer and Schreyögg (2014) who studied the relationship between hospital specialization and technical efficiency. They utilized several different measures of hospital specialization on data from German hospitals and compared the results in order to analyze whether or not different measures of specialization give varying results. The study utilized six measures of hospital specialization. Firstly the standard ITI, a distance-measure casemix based on a study by Zwanziger et al. (1996), a Herfindahl-Hirschmann Index modelled after Baumgardner and Marder

(1991), a Gini coefficient application developed by Daidone and D’Amico (2009) and two new specialization measures developed by the authors Lindlbauer and Schreyögg (2014) themselves, based on patient volumes instead of patient proportions as the first four. The study utilized the same one-step panel data model developed by Battese and Coelli (1995) that was also used by, amongst others, Rosko (2004). Lindlbauer and Schreyögg’s (2014) results indicated that measuring specialization by the standard proportion-based measures (ITI, Distance, HHI, Gini) is consistent as all four showed that specialization was negatively correlated with efficiency. The two new volume-based measures showed that specialization was positively correlated with hospital efficiency. Very contrasting results based on how one chooses to define hospital specialization (proportion or volume) yet consistent within its category. Comparing Lindlbauer and Schreyögg’s (2014) results to previous studies by the standard choice of specialization measure, ITI, they find that specialization reduces efficiency. This result is in direct contrast with, for example, Linna and Häkkinen’s (1999) findings of Finnish hospitals’ efficiency and also economic theory. The authors note, if only small hospitals can be considered specialized, why is it that large medical centers attract patients from all over the world? Lindlbauer and Schreyögg (2014) argue that the reason is that not all medical specialization is captured by the standard measures for hospital specialization, and they demonstrate this by creating two new measurements based on patient volumes – producing contrasting results on efficiency as well.

These contradictory results relating specialization and efficiency directly relate to the motivation behind this thesis’ research question – if specialization should lead to higher efficiency, why are larger university hospitals still preferred as treatment centers? Previous studies have lended credibility to this behavior in Finland and it is now of interest to focus on this relationship between efficiency and specialization again with a more recent panel of hospital performance data.

5 ESTIMATING THE EFFECT OF SPECIALIZATION ON COST EFFICIENCY AND MODEL CHOICE

Until this section, the reader should have an understanding of how a hospital operates and how its cost efficiency is measured against a frontier and how specialization is a factor of interest in that process. The previous sections also present the methodology commonly utilized in estimating cost efficiencies and the effect of specialization and highlight the relevant focal points of this study.

This section aims to summarize the empirical arguments for model choice to be applied on this thesis's data and acts as methodological basis for the empirical choices made together with points raised in the literature review.

Greene (2008) noted that previous studies have typically utilized a two-stage approach in order to estimate the effect of exogenous variables on efficiency. With DEA, a popular second stage regression model has been the Tobit regression (Greene, 1993) as the technical efficiency variable can be considered "censored" between the values 0 and 1, SFA has oftentimes been applied together with the parametric Ordinary Least Squares regression (Eastaugh 1992, Linna and Häkkinen 1999).

The two-stage approach was the standard until Wang and Schmidt (2002) showed that this approach yields heavily biased results. Wang and Schmidt (2002) confirmed that the bias in utilization of two-step procedures is severe and that this bias can be corrected for when using one-step frontier models that include the inefficiency-explaining exogenous variables in the frontier model specification. McDonald (2009) argued that the tobit regression as well was a problematic choice partnered with DEA. Thus one-step approaches with simultaneous estimations of the main cost function and the exogenous variables explaining the inefficiency are favored.

For panel data, Battese and Coelli (1995) developed their one-stage estimation model that included the independent variables explaining the mean of the inefficiency term directly in the main cost function, thus eliminating any bias or multiplying any estimation errors as in all previous approaches. The Battese and Coelli (1995) model has been utilized in the field ever since and has naturally been followed by other, more refined models, but for the purpose of estimating the effect of explanatory variables on efficiency with panel data – the one-step model is still popularized in the field as shown in the literature review. Lindlbauer and Schreyögg (2014), Rosko (2004) and Linna (1998) all applied the Battese and Coelli (1995) model in their studies and were the publications studying the most similar research questions to this thesis. Specific research conducted by Wang and Schmidt (2002) and Greene (2008) suggest that one-step estimation is the most appropriate approach empirically to analyze this research question in order to produce unbiased and reliable estimates of the coefficients.

Additionally, the Battese and Coelli (1995) model allows for estimation of unbalanced panel sets that is a requirement as the panel set studied in this thesis is unbalanced.

To summarize, this thesis chooses to apply the Battese and Coelli (1995) model and is motivated by 1) it being a one-step model, thus eliminating the double-biased estimates and 2) the inclusion of exogenous variables such as specialization and fixed variables such as hospital size proxy requires a one-step random effects model, 3) the allowance of unbalanced panel sets and 3) previous studies with similar data and research questions also utilized this model.

6 DATA

This section aims to present and explain the dataset that was analyzed in this study and the variables the dataset comprised of in addition to familiarizing the reader with the Finnish hospital sector.

6.1 COMPONENTS OF THE DATA SET

The dataset utilized in this thesis was compiled of two separate datasets in order to create a unique set for analysis.

One was originally a set comprised of patient-level data gathered from 48 Finnish hospitals over the years 2005-2013, aggregated to hospital-level. This privately owned dataset consisted of hospital-level aggregated DRG-weighted outputs (inpatient DRGs, outpatient DRGs, emergency DRGs, procedural DRGs and day surgery DRGs for each year), hospital-specific identifying information (hospital identifier code for each year, hospital type, hospital district) and data on hospital-specific characteristics (such as ITI).

In order to conduct an analysis on efficiency the previously mentioned output data for hospitals required the accompanying data for inputs. The data on operating costs for Finnish hospitals was extracted from the public hospital benchmarking database provided by the National Institute for Health and Welfare (THL) for the years 2011-2015. The variables extracted included: hospital identifier code, year, hospital district, operating costs (in Euros) and deflated operating costs (in Euros with baseline year 2011) for each year.

These two datasets were then combined by hospital identifier, year and district such that a unique dataset on Finnish hospital productivity for the years 2011-2013 was created. This dataset consisted of both output and input variables in addition to explanatory variables such as the degree of specialization to explain the operational differences between hospitals.

6.2 THE FINNISH HOSPITAL SECTOR

The Finnish hospital sector is mainly built around a public health care system divided into 20 hospital districts that are responsible of the provision of medical services to its appointed municipality’s citizens. Each hospital district then is comprised of a central hospital and smaller regional hospitals. (STM.fi 30.08.2018)

Specialized medical care is provided by the central hospital and tertiary care by the five national university hospitals that also act as central hospitals for their respective districts. Specialized medical care (surgeries, demanding examinations and treatments) is mainly provided by large public hospitals - monitored and steered on an aggregate nationwide level by Finnish Ministry of Social Affairs and Health (STM). More general and less intensive day surgeries are provided by private hospitals and the public health care system is supplemented by a private provision of care – in 2007 the share of private care was 1% while specialized care was 33% (THL, 2015).

Finland has steadily increased its share of GDP allocated to delivery of health care over the years: during 1980-1994 the share grew from 6,5% to 8,5% (KELA 1998) and in 2016 the share was 9,5% (THL 2016). Specialized care was allocated 35,3% of the spending. 73,8% of Finland's health care delivery was publicly funded in 2016 (THL 2016) and 26,2% privately. Municipalities funded 34,9% of the public costs. Funding is mainly based on municipalities' payments to hospital districts, according to the services used - see section 3.x.x. on Diagnostic-Related Groups. (Kautiainen et al. 2011)

In comparison to other Nordic countries, Norway (10,5% of GDP), Denmark (10,4%) and Sweden (11,0%) all allocated a higher share of their GDP to health care delivery than Finland in 2016.

The next section will present the variables in the dataset in closer detail.

6.3 DESCRIPTIVE STATISTICS AND VARIABLES

A summary table of the main variables is presented in table 6.3.1 below.

VARIABLE	MEAN	STD. DEV.	MIN	MAX	N
Costs	103000000.00	171000000.00	2033000.00	1020000000.00	139
Inpatient	101254.80	154193.30	1931.11	933071.00	139
Outpatient	70306.08	104759.00	1282.54	699566.80	135
Day surgery	7794.90	9878.51	283.34	60585.66	119
Procedures	96455.38	190739.1	94.62196	1230091.00	134
Emergency	56540.81	74303.21	189.39	432667.50	139
ITI	0.6570789	0.6135204	0.1432354	3.646736	139

Table 6.3.1: Summary statistics of the main variables

The dataset consists of 139 observations in total over a three-year period. There are 48 hospitals in an unbalanced panel.

Costs, refers to each hospital's total operating costs in euros, deflated to the sample period's starting year 2011. This automatically corrects against the inefficiency variable, u_{it}, capturing any effect caused by inflation.

No input price variables for labor or capital are included as the factor prices of these are set through central bargaining processes in Finland and can be considered equal to 1 in their effect on operating costs, they are they same for everyone and essentially no gains or market inequilibria exist, and the prices can be taken as exogenous.

Out of the output variables, inpatient services stand out as having the highest mean of 101254.80 DRG-adjusted units. Day surgery is a clear outlier with the lowest mean of 7794.90 units output. Outpatient services has a mean of 70306.08 units output. Procedures output makes up an output of 96455.38 of DRG-adjusted units while emergency services has a mean of 56540.81.

Some hospitals did not offer day surgery services at all, resulting in an unbalanced panel with only 42 observations for day surgery output. One hospital during one year also did not produce any procedures output as there are only 47 observations instead of the full 48. The rest of the outputs make out a full panel of 48 observations in addition to 48 ITI observations, totaling the full 139 observations over 3 years.

All of the output variables are DRG-weighted categorical outputs so that outputs are corrected for their input-intensity according to the NordDRG-definitions explained in previous sections and are expressed in DRG units as such. The categorical outputs are: inpatient services, outpatient services, emergency services, procedural services and day surgery services.

The different output categories are aggregated from individual patient-level records which consist of information regarding hospital visits, treatment episodes and as such are categorized into the different service categories. These individual-level records are aggregated to hospital level and adjusted for input-intensity.

Inpatient services are defined as an episode in which the patient is assigned a hospital bed while outpatient services do not necessitate a bed space. Medical procedures are an operational category as are day surgeries, with the latter being the more resource-intense by assumption and it is not provided by all hospitals in the sample. Day surgery is also clearly the outlier as an output by contributing only 2% to the total output. Emergency services by definition consist of the on-call services and emergency treatments.

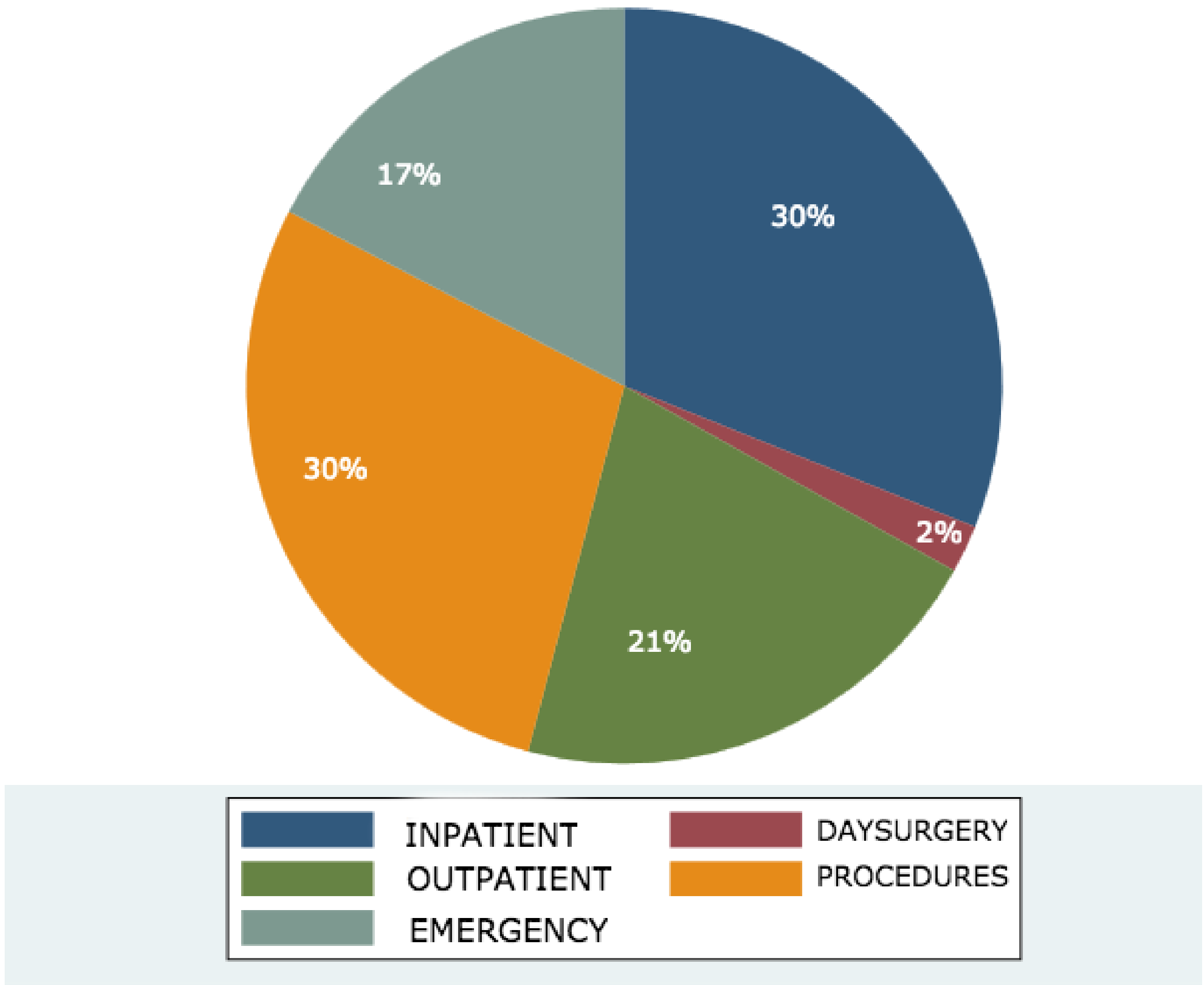

Figure 6.3.2: DRG-adjusted outputs produced as share percentages of total output (created with STATA 15).

The pie chart (graph 6.3.2) depicting the relative magnitudes of DRG-adjusted outputs of the different patient service categories in percentage shares in aggregate shows that inpatient services output (30%) and procedures output (30%) are equally vying for the largest output spot in total. Outpatient services output (21%) and emergency services output (17%) are not much smaller in terms of output magnitude. The only clear outlier is the day surgery output (2%) that is easily explained by the fact that not nearly all of the hospitals studied in this thesis offer day surgeries as a treatment option. Most medical operations done seem to be categorized into medical procedures output, based on the output pie chart, instead of day surgeries. In fact, while inpatient output is the largest output category, the fact that procedures is the second-largest may have implications while discussing the estimation results later in the thesis.

Out of 48 hospitals, 5 are university hospitals. The rest are either a municipal region's central hospitals (16), city health centers (12) or classified as type "other hospital" (15).

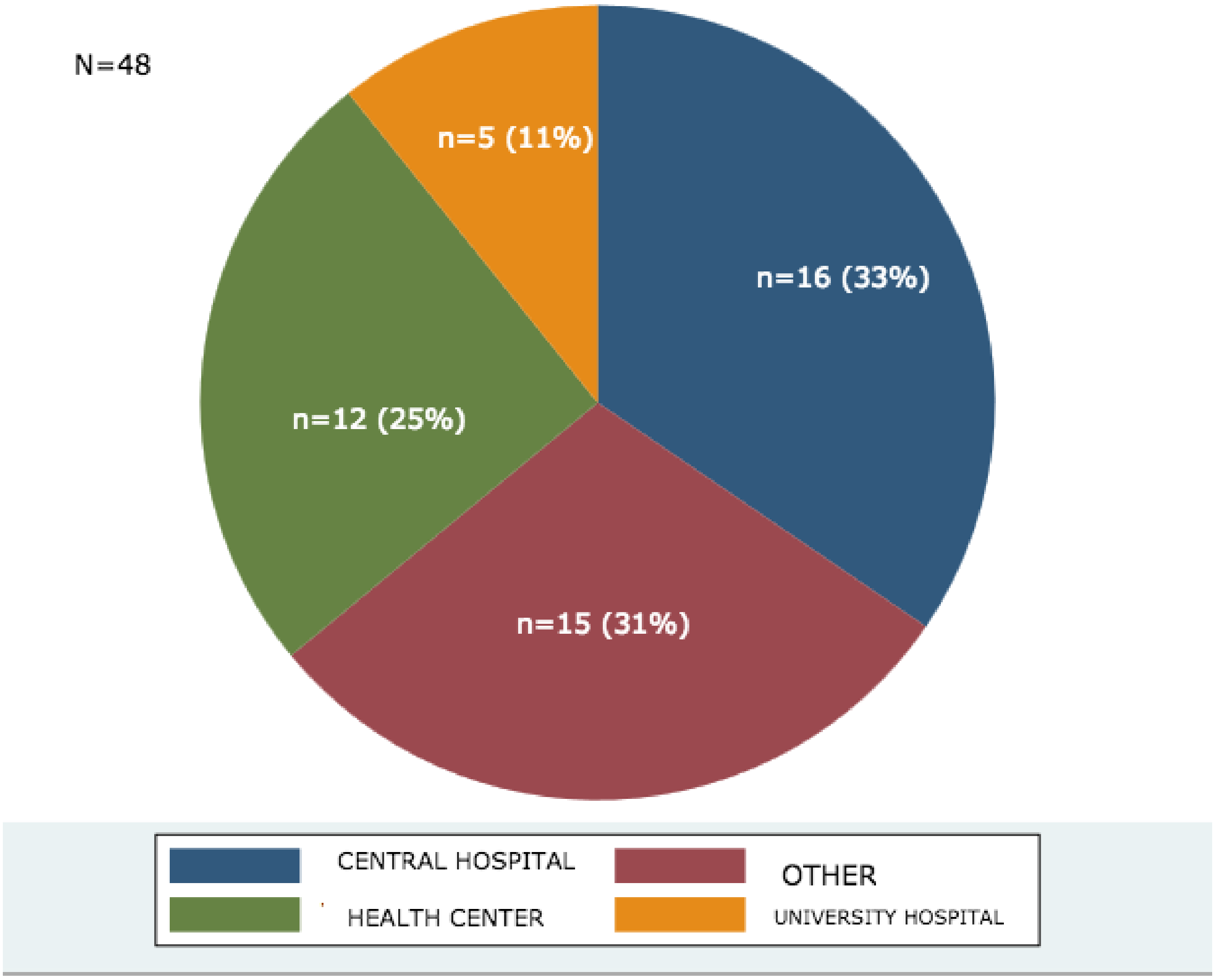

Figure 6.3.3: Hospital types (created with STATA 15).

University hospitals (11% of all hospitals) and central hospitals (33%) make up in total 36% of all hospitals (depicted in graph 6.3.3. above) that are guaranteed to offer day surgery services as treatment options. Health centers (25%) focus on providing mainly outpatient services. The hospital type "other" (31%) includes a wide range of hospital types and these hospitals may provide any, none or all of the output services.

The data set does not include psychiatric hospitals or military hospitals or similar specialized hospitals.

ITI is measuring the degree of specialization of each hospital in the sample, and reaches values from 0.14 to 3.65 with a mean of 0.66. The higher the concentration of medical specialization in a hospital, the higher the ITI value is. The mean indicates that most hospitals in the sample are not very specialized but that most hospitals have some minor degree of specialization.

The distribution of ITI values in the sample is depicted in the density distribution graph 6.3.4 below.

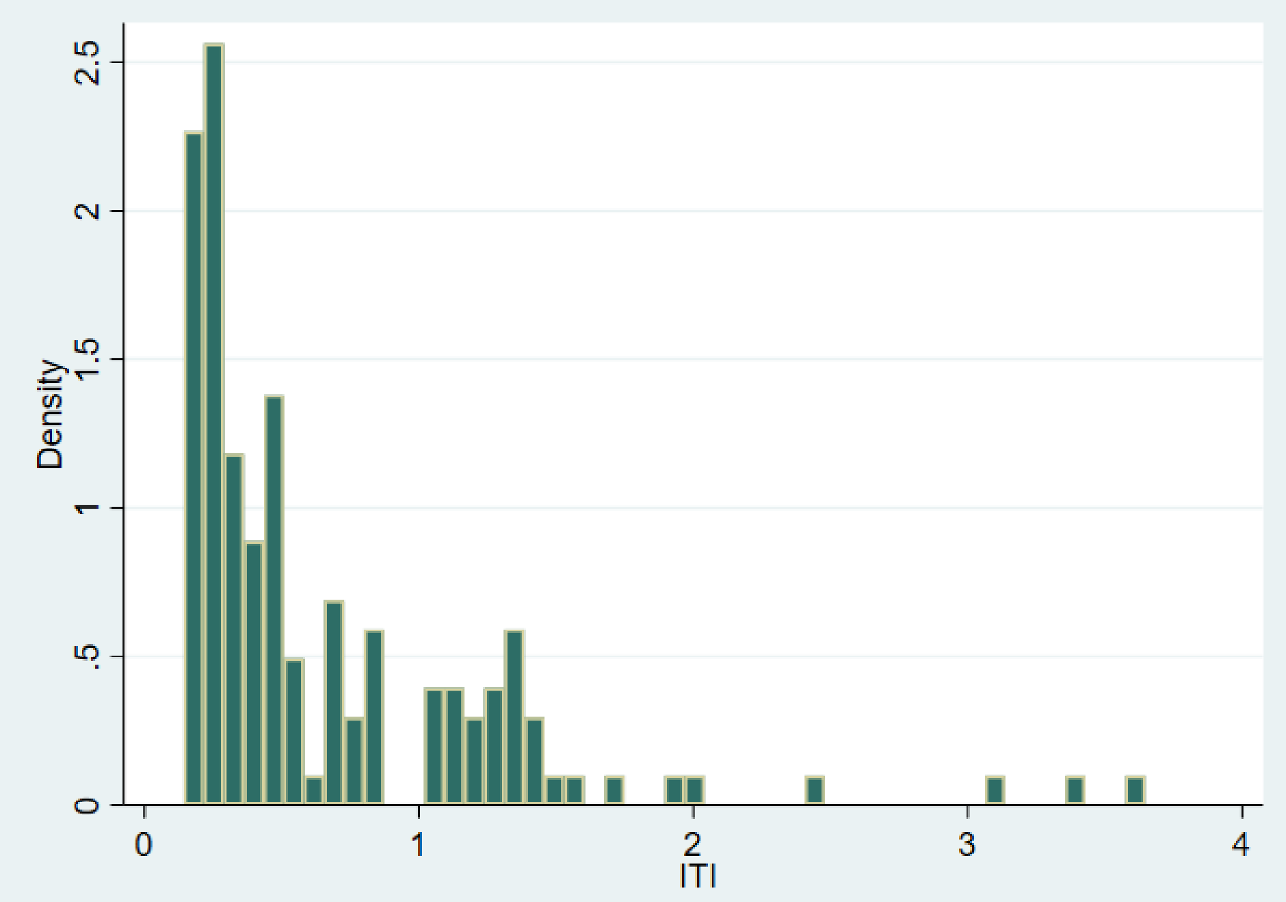

Figure 6.3.4: ITI distributional density (created with STATA 15).

The ITI distributional density graph shows that no hospitals are non-specialized at any point in the sample. The majority of hospitals have ITI values between 0.1 and 1 while several observations fall in the range between 1 and 2. Three observations are the clear outliers with highly specialized values, ITI values between 3 and 4.

7 MODEL SPECIFICATION

This section aims to present alternative specifications of the model and test which specification is the best fit statistically. Specification refers to choice of variables to be included in the model that is to be estimated. By the end of this section, one specification of the model is chosen, based on testing and the testing process is explained throughout the section so that the reader understands which variables are chosen into the model and why.

Due to previous research as discussed in the literature review and data section, a dummy variable depicting university hospital status was created from the data set specifically to be tested for its significance alongside specialization, ITI. University hospital status was created as a dummy variable (assigned a value of 1 if the hospital had the status of university hospital) and added into the dataset following the publications of Lindlbauer and Schreyögg (2014) and Linna (1998) who all raised the point of large university hospitals typically being an attractive target for medical tourists despite lacking a high a degree of medical specialization. The significance of this variable, which acts as a proxy for hospital size, is tested by the reasoning that large university hospitals in Finland are responsible for providing sole care in rare medical specialization categories and as such university hospital status may act as a proxy variable for hospital size, and even further capture some possible omitted variable bias. Therefore it was deemed reasonable to test a model specification that included university hospital status as a variable in addition to ITI.

The validity of including ITI and university hospital status as independent explanatory variables in the inefficiency model was tested by running LR-tests[1] between a frontier model without any explanatory variables in the inefficiency model (blank inefficiency frontier) and models with only ITI as an explanatory variable in the inefficiency model, or both ITI and a university hospital status dummy as explanatory variables in the inefficiency model.

[11] The likelihood ratio test is conducted by comparing the goodness-of-fit between two models such that the other is a restricted (s=simple) version of the unrestricted (general=g, more parameters) version of the other. The deviation between the two is calculated $LRT=-2\log_e(L_s)+2\log_e(L_g)$, where L refers to the log likelihood function. The test statistic LRT is chi-squared distributed as a random variable with degrees of freedom equal to the difference in parameters between the two models.

Model 1 (with specialization, ITI, and hospital size, university hospital, included):

(7.1) $\ln Costs_{it} = \alpha + \beta_1 \ln(Inpatient)_{it} + \beta_2 \ln(Outpatient)_{it} + \beta_3\ln(Daysurgery)_{it} + \beta_4\ln(Procedures)_{it} + \beta_5\ln(Emergency)_{it} + u_{it} + v_{it}$,

where

(7.2) $u_{it} = \delta_0 + \delta_1 ITI_{it} + \delta_2 University_{it}\ V_{it}$

Model 2 (with specialization, ITI, only):

(7.3) $\ln Costs_{it} = \alpha + \beta_1 \ln(Inpatient)_{it} + \beta_2 \ln(Outpatient)_{it} + \beta_3\ln(Daysurgery)_{it} + \beta_4\ln(Procedures)_{it} + \beta_5\ln(Emergency)_{it} + u_{it} + v_{it}$,

where

(7.4) $u_{it} = \delta_0 + \delta_1 ITI_{it} + V_{it}$

Model 3 (with no inefficiency-explanatory variables):

(7.5) $\ln Costs_{it} = \alpha + \beta_1 \ln(Inpatient)_{it} + \beta_2 \ln(Outpatient)_{it} + \beta_3\ln(Daysurgery)_{it} + \beta_4\ln(Procedures)_{it} + \beta_5\ln(Emergency)_{it} + u_{it} + v_{it}$,

Likelihood-Ratio Tests

Model 3 nested in Model 2	**LR chi2 (2) = 23.45. Prob >chi2 = 0.0000**
Simple model nested in model with ITI as explanatory variable H_0: Simple model is a better fit	Result: Reject H_0, ITI should be included

Model 2 nested in Model 1	**LR chi2 (1) = -12.55. Prob >chi2 = 1.0000**
ITI model nested in model with ITI and University as expl. Variable H_0: Model with only ITI is a better fit	Result: Accept H_0, ITI should be included, reject University.

Table 7.1: Likelihood-ratio tests.

The null hypothesis in each case refers to the parameters of the more complex model as being statistically zero and thus the restricted model should be favored over the more complex specification. The null hypothesis is rejected whenever the chi-squared value is large enough and thus the probability of the additional parameters being statistically zero is less than 5%.

The results follow the main estimation results by highlighting the significance of specialization as an explanatory variable in contrast to the lack of significance that university hospital status carries with their respective effect on inefficiency.

The null hypothesis for an LR-test is that adding the additional parameters and thus generalizing the restricted model into a more complex one statistically worsens the goodness-of-fit of the model.

The first LR-test was run by between models 2 and 3, with model 3 (no explanatory variables) nested into model 2 (specialization as an explanatory variable for inefficiency), and the LR-test clearly rejects H_0 of simplifying the model and not including ITI as an explanatory variable.

Alternatively, when nesting model 2 into model 1 (with both ITI and university hospital status as explanatory variables for inefficiency) the null hypothesis of not expanding the model to include university hospital status as well is clearly accepted.

To summarize, regarding model specification these likelihood ratios suggest that specialization (ITI) should be included as an explanatory independent variable in the inefficiency model whilst university hospital status does not statistically increase the goodness-of-fit of the model. Additionally, failing to include ITI as an explanatory variable in the inefficiency model is strongly suggested by the LR-tests to lead to an overly parsimonious model that may suffer from omitted variable bias and thus lead to biased estimates, especially of inefficiency.

8 ANALYSIS

This section presents our estimation results for our data presented in the previous sections and estimated here with the time-varying one-stage Battese and Coelli (1995) inefficiency model. The model allows for unbalanced panels and as such is additionally preferred for estimation. The model assumes Hicks-neutral technological evolution and thus a time trend variable is included (T). The results show that inefficiency is associated with higher levels of specialization and Finnish hospitals' cost efficiencies range between 22-97%.

8.1 ESTIMATION RESULTS

An additional time trend variable, T with a coefficient τ, was added to the function to control for technological progress over the short panel time instead of time dummies as the panel is short, only three years, and a time trend was considered appropriate to control for Hicks-neutral technological change (Battese and Coelli 1995) and other, non-specific exogenous shocks (Jacobs et al. 2006).

The model was estimated in logarithmic form, by taking natural logged values of all the output variables in the frontier model as well as the dependent variable, total costs, as all variables are in non-negative values and in order to make evaluation of results more straightforward.

Due to the LR tests indicating that university hospital status should not be included in the model specification as an explanatory variable for inefficiency but specialization should be, the Battese and Coelli (1995) model was estimated with specialization as an explanatory variable for inefficiency only.

The Model

Estimating

(8.1) $\ln \text{Costs}_{it} = \alpha + \beta_1 \ln(\text{Inpatient})_{it} + \beta_2 \ln(\text{Outpatient})_{it} + \beta_3 \ln(\text{Daysurgery})_{it} + \beta_4 \ln(\text{Procedures})_{it} + \beta_5 \ln(\text{Emergency})_{it} + \tau T + u_{it} + v_{it}$,

where

(8.2) $u_{it} = \delta_0 + \delta_1 ITI_{it} + V_{it}$, and t=1, 2, 3 where all variables are defined as before the main estimation results are depicted in table 8.1.1 below.

Coefficients	ln $Costs_{it}$ LogL=-1.0322
ln($Inpatient_{it}$)	0.794*** (0.000)
ln($Outpatient_{it}$)	0.020 (0.788)
ln($Daysurgery_{it}$)	0.116 (0.094)
ln($Procedures_{it}$)	0.120* (0.034)
ln($Emergency_{it}$)	0.021 (0.767)
T	-0.008 (0.762)
Constant	6.307*** (0.000)
ITI	37.955*** (0.000)
$\hat{\boldsymbol{\delta}}_0$	-59.500
λ	12.036*** (0.000)
$\hat{\boldsymbol{\sigma}}_u$	2.292*** (0.000)
$\hat{\boldsymbol{\sigma}}_v$	0.190*** (0.000)

p-values in parentheses. * p<0.05,** p<0.01, *** p<0.001

Table 8.1.1 Estimation results of Model 1 (Battese and Coelli (1995) with only ITI)

The first noteworthy result here is that the signal-to-noise ratio (λ, the variance ratio of inefficiency to random noise contributing to the residual's variance) is statistically significant in this model with respect to both inefficiency and noise. Lambda has a value above 12, so there is inefficiency found in the sample's hospitals (a value of zero would indicate no inefficiency to be present). Lambda is calculated as the ratio of $\lambda=\hat{\sigma}_u / \hat{\sigma}_v$ and as such the value of 12.04 shows the inefficiency contributing heavily to the residual's variance in relation to noise effects. However, the effects caused by noise are also statistically significant and thus are not entirely captured by the model.

The coefficients of all output categories are positive and thus follow intuition: increased output increases a hospital's operating costs.

Inpatient services and procedures along with day surgery contribute more to operating costs relative to outpatient services and emergency services. Inpatient services contribute to a hospital's costs by a much larger share than the other output categories, by a coefficient factor of 0.79, which is also statistically highly significant. Outpatient services, in comparison, only have a coefficient of 0.02, which is also the coefficient of emergency services – these outputs have roughly the same magnitude of an effect on costs and the effect is statistically rather weak - at least compared to inpatient services. Output from medical procedures has a coefficient of 0.12 and it is statistically significant. The constant has a significant coefficient of 6.30 and represents the costs that would be incurred in the case no outputs were produced at all.

The time trend variable has a negative coefficient indicating that the costs decreased slightly over the time period. The time trend variable has a negative coefficient indicating that the operating costs have tended to decrease over the three-year period by a small, statistically insignificant amount.

The degree of specialization (ITI) has a positive effect on cost inefficiency. ITI has a coefficient of 37.96 and it is statistically significant at 0.1% significance level. The result indicates that as a hospital's degree of specialization, measured here by ITI, increases so do its costs. This result is in stark contrast to economic intuition but may be explained by the peculiar structures of the Finnish hospital system as large university hospitals may in fact benefit from economies of scale in this data.

8.2 COST EFFICIENCY ESTIMATION RESULTS

Calculating the cost efficiencies and summarizing the overall cost efficiency of the hospitals in the sample are shown in table 8.2.1 below.

VARIABLE	Mean	Standard dev.	Min	Max	Observations
Cost efficiency	0.868662	0.1247328	0.2240445	0.9699303	N=117, n=42

Table 8.2.1: The cost efficiency summarized.

Individual cost efficiencies are obtained according to the truncated normal distribution due to it being the general case (with respect to the half-normal distribution) and the equation given in (3.3.2.5) $CE_{it} = \exp(u_{it}) = \exp(z_{it}\delta + V_{it})$

Cost efficiencies were also calculated with the half-normal distribution estimator by Jondrow et al. (1987) and the values estimated were approximately the same so the results from the normal distribution were chosen to be presented.

Due to estimating logged values, the cost efficiency estimates can be interpreted as percentage differences from the frontier (Jacobs et al. 2006). The mean cost efficiency is 87% with the least efficient hospital reaching a low of 22% and the most efficient hospital reaching a cost efficiency of 97%. The large variance in this calculation may be a consequence of a somewhat parsimonious model not capturing all the variance in the data but individual observations will be studied via a distribution density graph on the next page. Some observations are dropped as some hospitals lacked certain categorical output for in all years and cost efficiency could not be calculated for each year in these cases - highlighting the importance of model specification and sensitivity tests with stochastic frontier analysis by managing to estimate the cost efficiency of nearly each hospital in the sample, n dropped from 48 to 42 only in total. A lack of reliable data or misspecification of the model could result in a much larger drop in the number of observations and therefore inconsistent estimates of cost efficiencies.

With a mean of 87% cost efficiency, the indication is that more hospitals than not are rather cost efficient. The hospitals reaching very low values of cost efficiency (22%, for example) are rather the anomaly and on average, Finnish hospitals in the sample are mostly cost efficient.

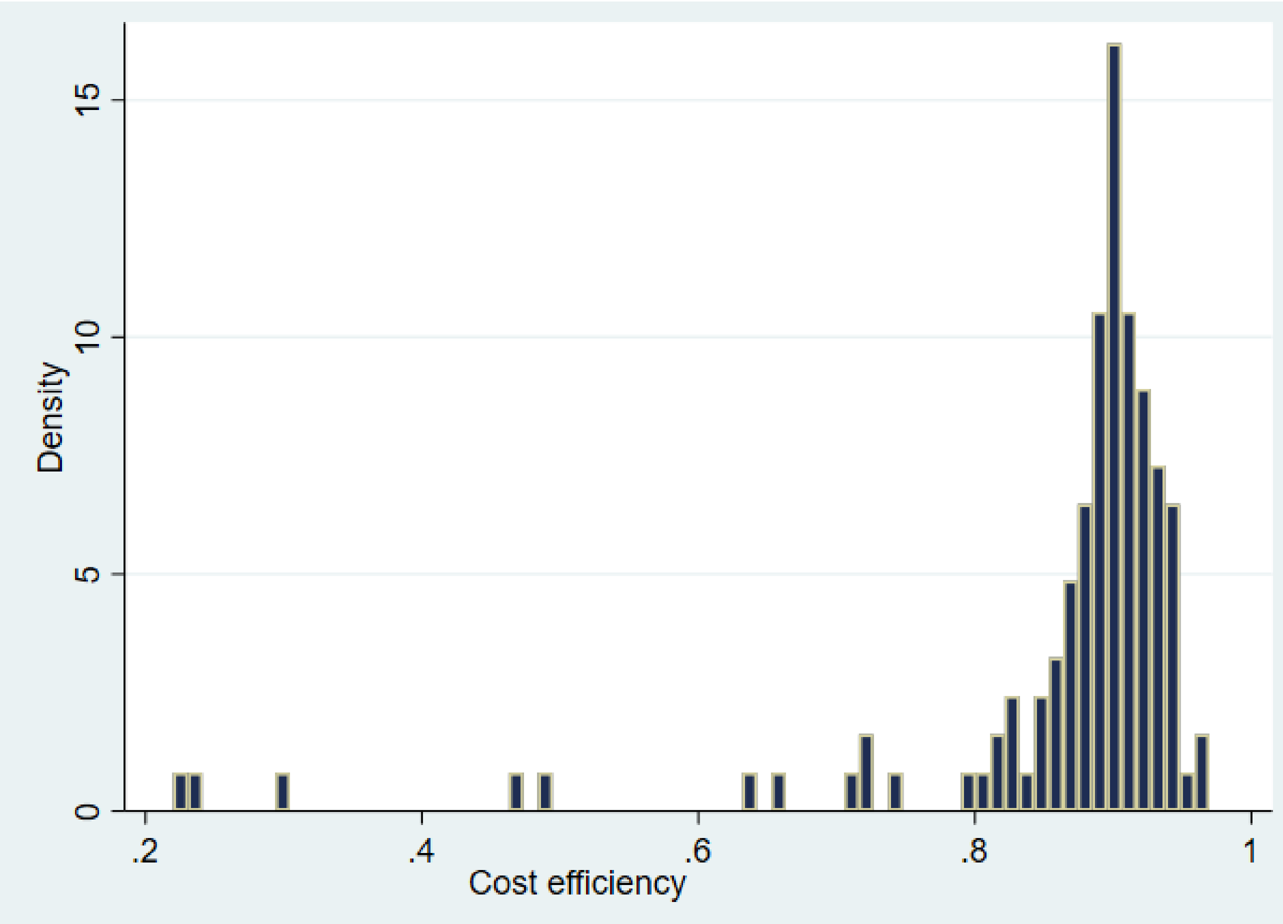

Figure 8.2.2: The densities of the distribution of cost efficiencies of the sample's hospitals (created with STATA 15).

The graph above is showing the distribution of cost efficiencies of the sample's hospitals, confirming that most hospitals display rather high cost efficiency and thus the mean is 87% and the majority of hospitals are closer to the most efficient hospital (with 97% cost efficiency) in efficiency than the least efficient hospital (with 22% efficiency). In fact, the observations in the vicinity of 22% cost efficiency are singular observations: one observation of 22%, one observation of 23% cost efficiency, one nearing 30% cost efficiency and a few in the middle range of 45-70% cost efficiency. These are all singular observations, though, and the majority of observations lie in the 80-95% cost efficiency range.

8.3 THE EFFECT OF SPECIALIZATION ON COST EFFICIENCY

Regarding cost efficiency, the degree of medical specialization (ITI) has a significant positive effect on a hospital's cost inefficiency. The more specialized a hospital is the more inefficient it also is. A possible explanation for this may be found in the structure of Finnish hospitals – it is possible that the ITI measure allocates higher specialization levels to university hospitals as they are the only ones producing specialized medical care in Finland and are definitely thus producing very expensive DRG outputs due to the fact. Another explanation may be that neither the data set nor the model succeeds in taking into account economies of scale that may be present at all of the hospitals and thus attributes biased efficiency values to less specialized hospitals.

Referring to the density distribution graphs for both ITI and cost efficiency, it is known that overall the Finnish hospitals in the sample are cost efficient and not very specialized. Delving into the results regarding the non-intuitive result of specialization increasing cost inefficiency, some peculiar cases can be pointed out as case studied of interest. For example, hospital 90615's cost efficiency and ITI value relationship is depicted in graph 8.3.1 below.

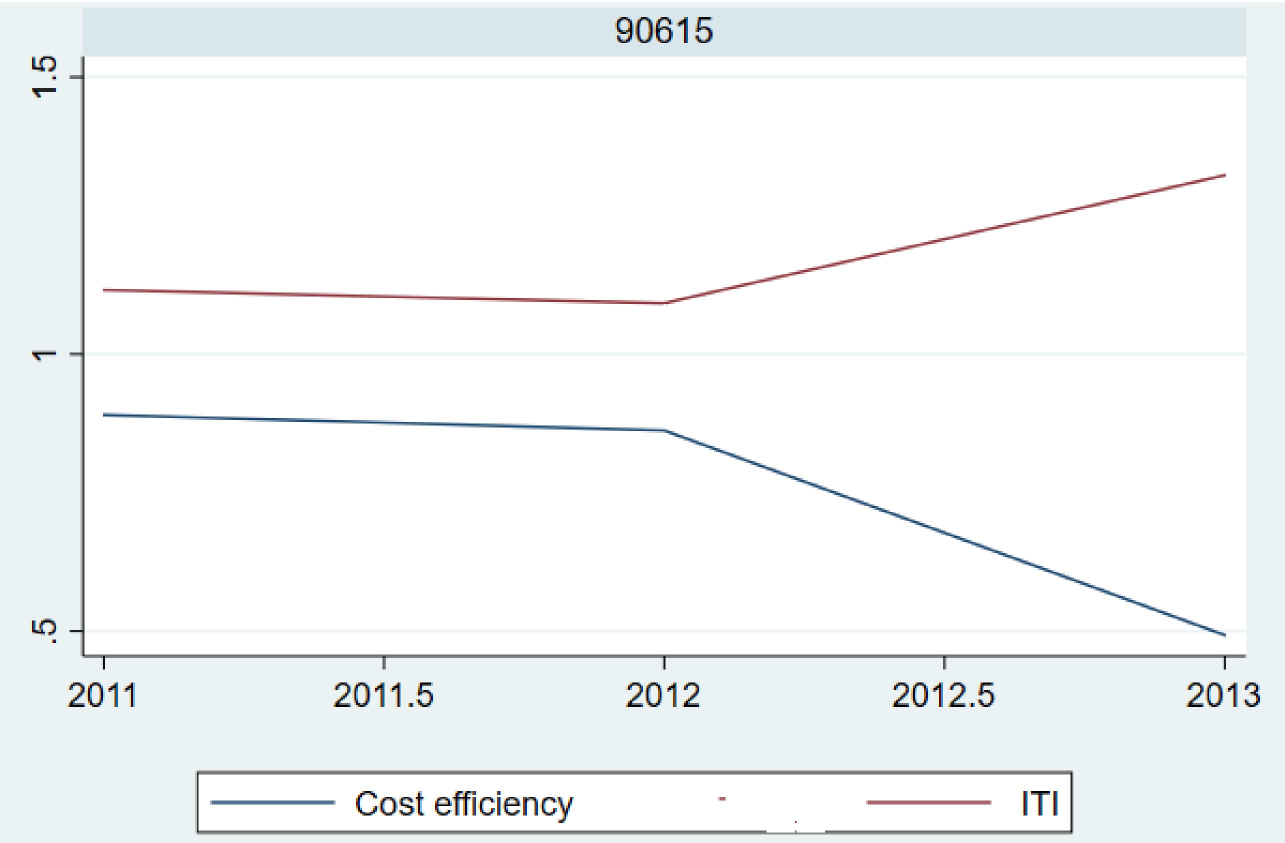

Figure 8.3.1: Hospital 90615's ITI and cost efficiency during 2011-2013 (created with STATA 15).

Hospital 90615 has an ITI of slightly above 1 in 2011, the starting year of this thesis's study period, and a cost efficiency score of slightly below 100%, but nearly 90%. This hospital is very cost efficient and also somewhat specialized, not highly so though. Following the overall analysis's results, from 2012 to 2013, the hospital starts to specialize on a clear trajectory and in a direct relation, its cost efficiency begins to sink downwards, reaching a low of around 50% only in 2013. The hospital has nearly halved its cost efficiency in only two years, while increasing its specialization concentration index by almost a third.

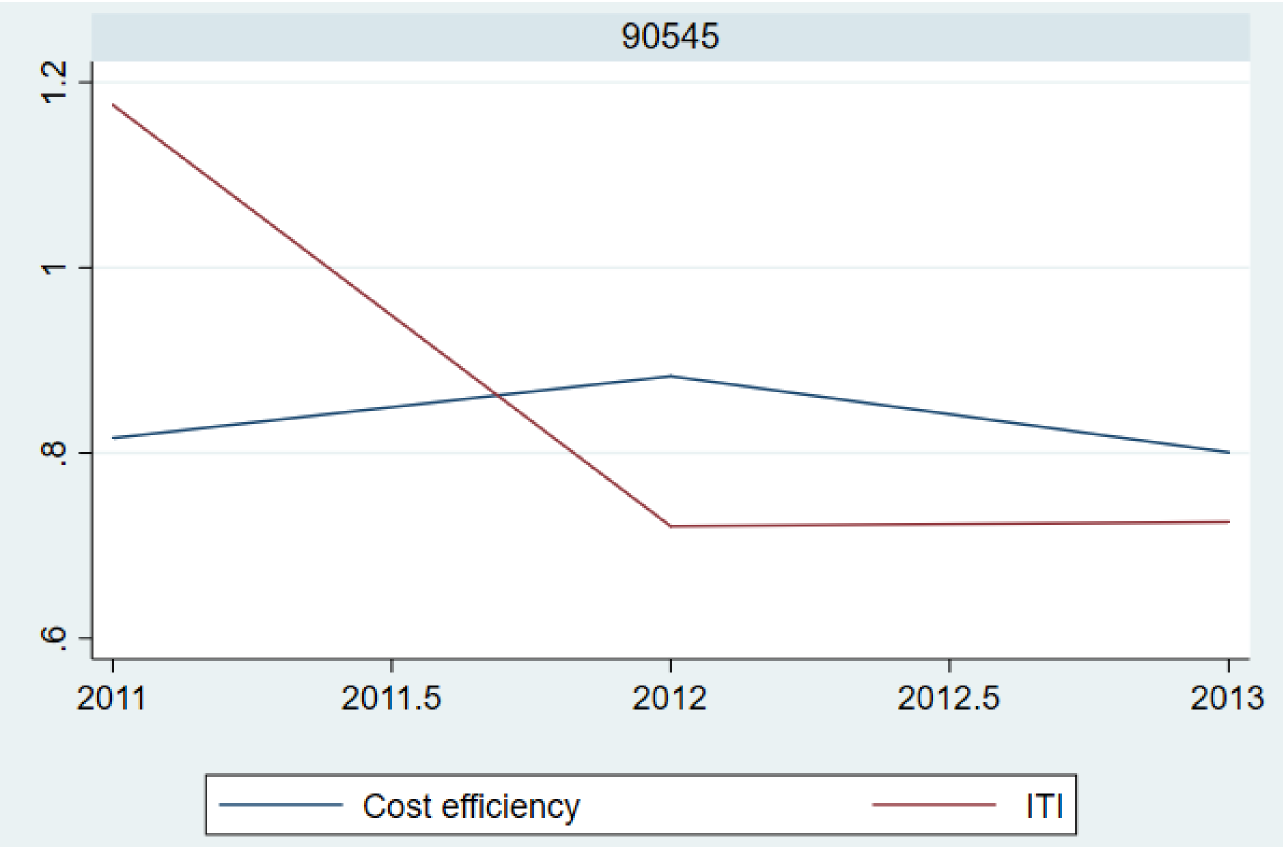

Figure 8.3.2: Hospital 90545's ITI and cost efficiency during 2011-2013 (created with STATA).

Above in graph 8.3.2 is another case study of hospital 90545 in the sample with initial starting values of ITI nearing 1.2 (somewhat specialized) and a cost efficiency score of approximately 81%. This hospital holds its cost efficiency score relatively stable through the sample period 2011-2013 despite generalizing its operations heavily from 2011 to 2012. Its ITI value drops from 1.2 to around 0.7 in that one year and simultaneously causes a small positive bump in cost efficiency, increasing it from 81% to nearly 90% before it drops again to 80% in 2013 with ITI stabilizing to its newfound lower generalist level of 0.75. This hospital confirms the overall estimation results of specialization being associated with lower cost efficiency.

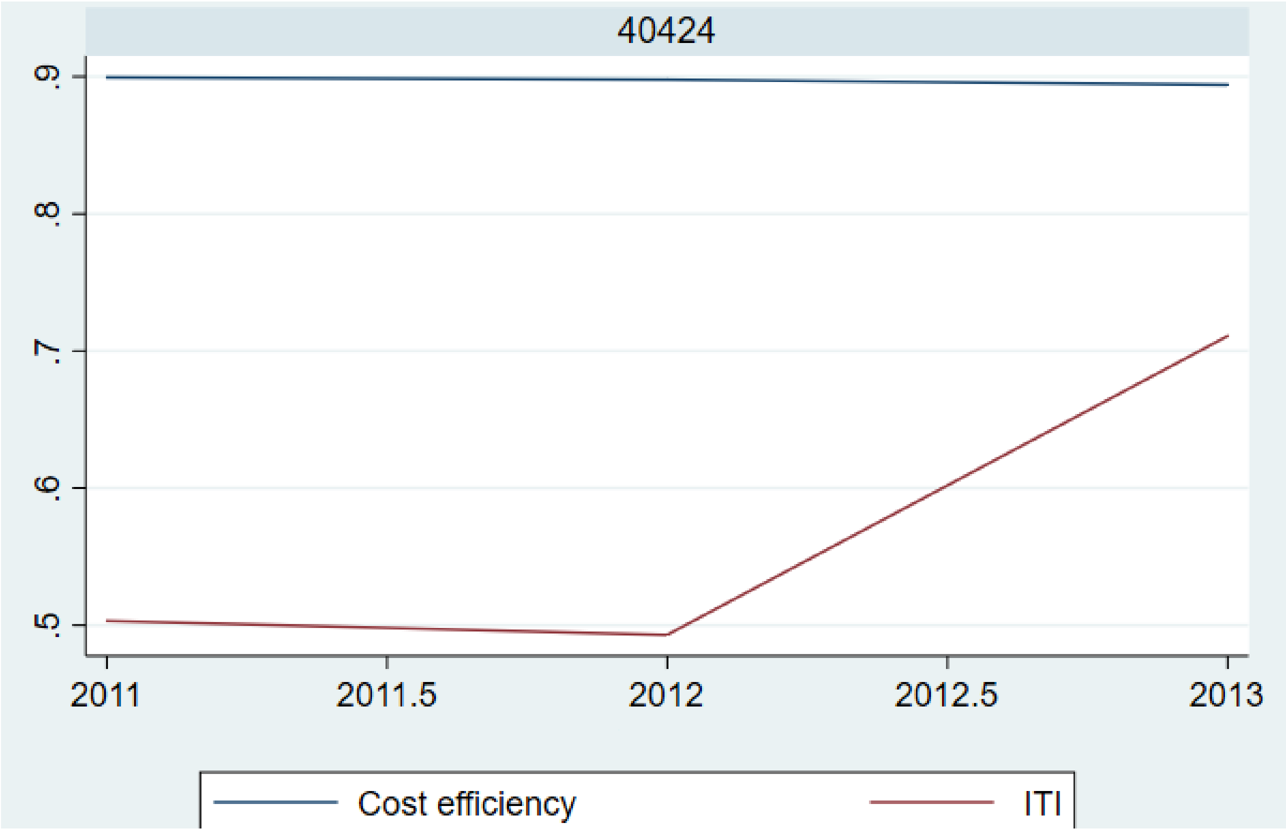

Figure 8.3.3: Hospital 40424's ITI and cost efficiency during 2011-2013 (created with STATA 15).

Hospital 40424 (depicted in graph 8.3.3) is another outlier with a steady extremely high cost efficiency score of 90% from 2011 to 2013 despite its ITI value increasing rapidly from a low 0.5 in 2011 and 2012 to above 0.7 in 2013. This hospital's cost efficiency is unaffected by changes in its degree of specialization and is an outlier in this thesis's sample trend.

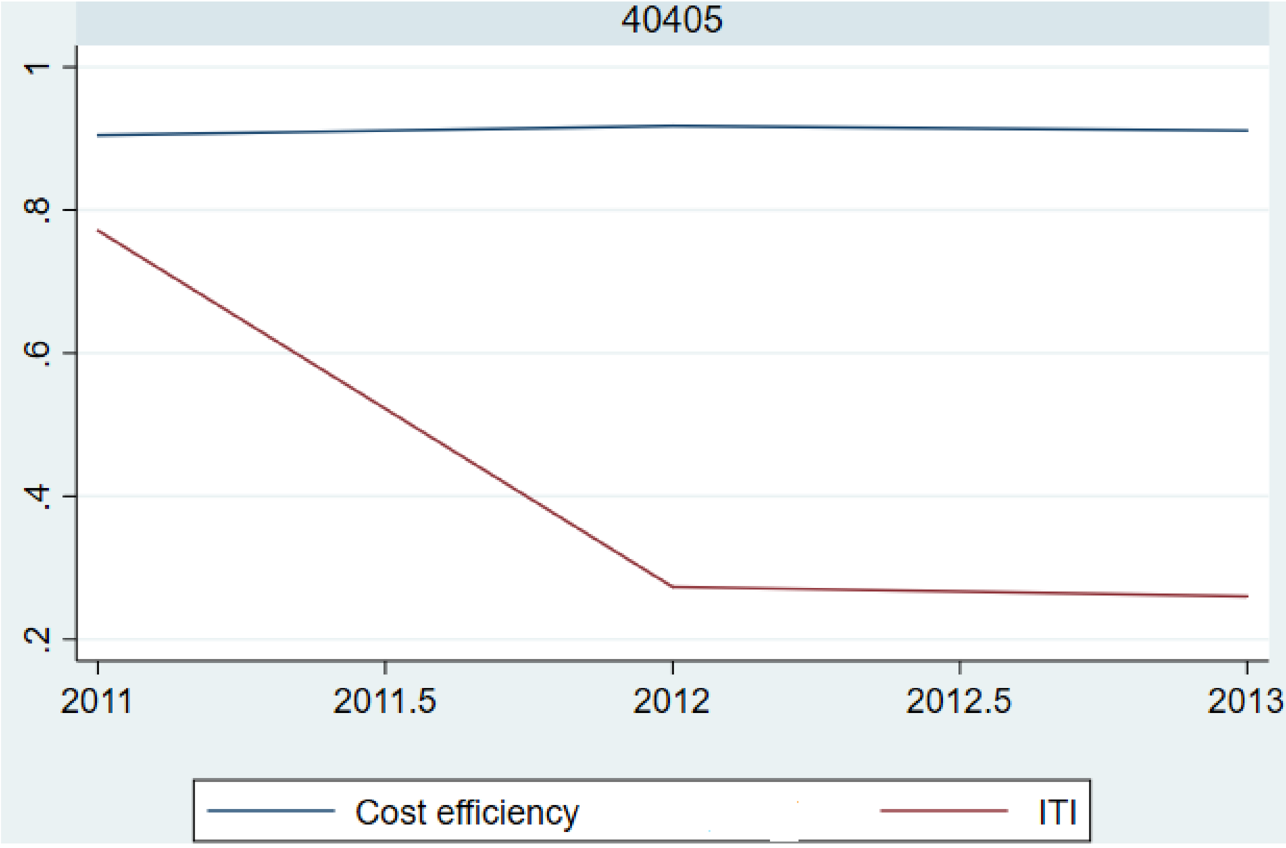

Figure 8.3.4: Hospital 40405's ITI and cost efficiency during 2011-2013 (with STATA 15).

Hospital 40405 is chosen as a case study to contrast the previous case, hospital 40424. As hospital 40424 held a steady 90% cost efficiency despite increasing its level of specialization, this hospital 40405 experiences a large reduction in its degree of specialization, and has generalized its medical operations from 2011 to 2012. Initially, hospital 40405 has a cost efficiency of around 90% and an ITI value of 0.8 which means that the hospital is likely operating more heavily in certain medical specialization categories but is not defined as specialized or a generalist. During 2011 hospital 40405 becomes a generalist and begins operating on a much wider scale of medical categories, thus reducing its ITI value to 0.3. Similarly to hospital 40424, this hospital's cost efficiency also holds completely steady at 90% despite the significant change in ITI – in contrast to the previous hospital, the change is in the opposite direction, yet both hold constant cost efficiencies. The indication is, ITI has a very small effect on cost efficiency for these two hospitals.

9 DISCUSSION

This thesis has estimated the cost efficiency of Finnish hospitals and the effect specialization has on cost efficiency utilizing stochastic frontier models. As mentioned in the previous section, the results do not reflect straightforward economic intuition as specialization is associated with low cost efficiency but provide further material to existing debate over similarly contrasting results. I find that the cost efficiencies of Finnish hospitals over the years 2011-2013 vary by a rather large margin, 22-97% but that the majority of hospitals operate with a high level of cost efficiency and that the mean of cost efficiency is 87%, and while specialization is positively associated with lower cost efficiency, most hospitals exhibit low levels of specialization overall. I also demonstrate the steps I took to compile this dataset, choose the variables to estimate, choose and specify the model and demonstrate the model estimation results.

Regarding the estimation results presented in this thesis, some discussion should follow to analyze them more thoroughly. The model was estimated in natural logs and thus can be interpreted in percentage shares. Of all the input categories contributing to the hospitals' operating costs annually, inpatient services are found to contribute the most by a large margin: a coefficient of 0.8 in comparison to the second largest coefficient of 0.12 of procedures and day surgery. An increase of 1% of a hospital's inpatient output will increase its operating costs by 0.79% holding everything else constant. Similarly, a 1% increase in a hospital's procedures or day surgery output will increase its operating costs by 0.12%. This result gives significant implications on the importance of a hospital's efficiency within its inpatient services. While procedures output contributes nearly an equal amount to total output as inpatient services in absolute units, its coefficient is only 0.12 indicating that a 1% increase in procedures output increases a hospital's operating costs only by 0.12% in comparison to inpatient services' 0.79%. The difference is noteworthy and indicates a distinct area of focus within inpatient treatment for hospital management.

Inpatient output and procedures output are the only outputs that have a statistically significant effect on costs and the most logical reason for this is found in the descriptive data section; inpatient services and procedures output both make out approximately a 30% output share of the aggregated output in total each and thus it is most likely the reason why the two largest output contributors are the most significant explanatory factors. This result implies that inpatient services contributes in a more significant effect to a hospital's costs and furthermore, efficiency gains are more likely to be found in inpatient services.

Naturally, inpatient output contributes significantly to costs is the fact that all hospitals in the sample provide inpatient services whilst not every hospital provides medical procedures but the difference cannot necessarily be considered large enough to be responsible for such a difference in coefficients (both outputs make out approximately 30% of total output, all hospitals provide inpatient, one hospital did not produce procedures output). Inpatient services affect hospital costs by a considerable margin – the effect is over six times the magnitude of the second most significant output category, procedures – and therefore inpatient services is the hospital service category where Finnish hospital gain or lose cost efficiency. Compared to outpatient and emergency services, which contribute significantly less – a 1% increase in either output increases costs by 0.02%, ceteris paribus - inpatient services is the clear outlier. These results bear an indication policy-wise for decision-makers to focus on hospital policy planning which increases the efficiency of inpatient services and most likely optimizes treatment chains in healthcare in a fashion that patients can be treated in other treatment categories, such as outpatient services, in a more efficient capacity.

This reason why inpatient may be so significant compares to the other categories is that the sample of 48 hospitals consists of university hospitals, health centers and regional hospitals. A common service denominator is inpatient services that all sample hospitals produced output in (N=139) as opposed to, for example, procedures output, which some hospitals did not produce at all. It is a reasonable assumption that outpatient services use up fewer resources than inpatient services simply by being less resource-heavy but by adjusting the outputs with DRG weights should correct for any bias, in theory. Day surgery output has a coefficient of 0.12 rounded up, the same as procedures output, indicating that a 1% increase in day surgery output increases operating costs by 0.12% ceteris paribus. Day surgery output makes up only 2% of total output and the difference reflects the intensity of resources that surgical operations require in comparison to the other output categories. But while inpatient services are offered by every hospital, day surgery services are a provided in a varying magnitude and variety. However, one must note, the DRG weighting system may be exhibiting some bias when used as a method for aggregating hospital treatments into single outputs (Linna and Häkkinen 1999) and as such may have some effect on the estimated effects. For example, day surgery being a resource-intense and thus consists of so-called “heavy” DRGs, may be weighted such that the heaviness of the DRGs is not fully consistently reflected in the weights.

Overall the results show that a higher degree of specialization is associated with lower levels of cost efficiency. The Finnish hospitals in the sample have a mean cost efficiency of 87% in the period 2011-2013 and a mean level of specialization (ITI) of 0.66. The value of ITI indicates a relatively low degree of specialization overall while the mean cost efficiency of 87% indicates that Finnish hospitals overall are relatively cost efficient. Compared to previous research conducted in other countries, Finnish hospitals are more cost efficient relative to international levels of cost efficiency; for example in comparison to the foreign research conducted by Wagstaff (1989) who found that Spanish hospitals had cost inefficiency levels of 28% indicating much lower levels of cost efficiency than 87%. My findings of cost efficiency of 87% are in line with the previous results of Linna and Häkkinen (1999) though, who found that Finnish hospitals exhibited relatively high cost efficiency scores from 0.86 to 0.93.

The rather low degree of specialization of hospitals in the sample may reflect the overall nature of Finnish hospital in the public sector which the sample consisted of in large. Finnish hospitals in general in the public sector have to act as generalists in the sense that they must provide health care services and emergency services to a degree to their municipality's citizens and direct more specialized cases to university hospitals. As this assumption was a possibility, some singular hospital case studies were studied in more detail and the relationship between cost efficiency and ITI and how the relationship behaved during 2011-2013. These cases showed that the previous assumption of generalist hospitals and high cost efficiency is most likely too simplified an assumption. Several of the hospitals in the sample experienced significant changes in their ITI values during the time period yet either no change in their cost efficiency or significant change in their cost efficiency.

Yet another point of interest is the effect of hospital type and size, as testing rejected the inclusion of university hospital type as a variable as it did not improve the model's statistical fit and as such university hospital status is not a statistically significant explanatory factor in this model. This is another contradiction in comparison with previous studies that consider the possibility of large university hospitals distorting the effect specialization has on cost efficiency by some hidden effect. The results in this thesis indicate that the five Finnish university hospitals at least bear insignificant effects on specialization's effect on cost efficiency by university hospital status alone relative to other types of hospitals – suggesting that while specialization and cost efficiency are correlated negatively, the relationship is not directly influenced by a third variable, university hospital status, in a triangle fashion. Thus the question remains as to what factor could be indirectly affecting the relationship between specialization and cost efficiency: the answer may lie in the definitions of specialization and efficiency themselves.

The effect of specialization on hospital performance is a current topic of interest in health care research and the results in this thesis follow the lines of the questions of interest Lindlbauer and Schreyögg (2014) raise in their paper. They found that the traditional measures of specialization, based on patient proportions, were negatively correlated with efficiency and raised the question; do these measures account for specialization accurately? By measuring specialization based on patient volumes, the results were contradictory to the previous ones – specialization was now positively correlated with efficiency. The fact that most medical specialties have treatment clinics only at the large university hospitals in Finland may distort the perception of specialization the traditional measures create.

As Linna (1998) and Linna and Häkkinen (1999) have found previously that Finnish hospital's cost efficiency is positively correlated with specialization, my findings contradict those results and raise two interesting points; how big of an effect does time-series analysis have relative to cross-sectional analysis and did Finnish hospitals become less cost efficient during the 15 years that span in-between the studies? The first question must be answered by noting that the cross-sectional studies are most often conducted by DEA and thus are known to result in higher efficiency estimates in some cases (Nunamaker 1985). The second question is up for debate – in 1994 the Finnish health care system consumed 8.5% of Finland's GDP vs. 9.5% in 2016. Linna (1998) estimated that cost efficiency scores were between 0.88-0.90 in the years 1988-1994 and compared to the efficiencies for the years 2011-2013 with efficiencies ranging between 22% and 97% - in addition to Linna and Häkkinen (1999) finding cost efficiency scores of 0.86-0.93, it is perhaps indicative of reduced cost efficiency overall that is reflected in my findings of specialization increasing inefficiency. This assumption alone is hardly explanative of the entire phenomenon though as the distributional density of the cost efficiencies estimated in this thesis are of the right-hand-tail variety with a mean of 87% and heavily gathered near the high-efficiency end rather than the low-efficiency side.

To comment on the limitations of this study, there is a lack of data variability first and foremost. As the estimation results suggest from the frontier model, both the inefficiency variance and the noise variance contribute significantly to the overall noise in the model and as such indicate the possibility of omitted variables (hospital variables, employee profile, municipality profiles, etc.). As the dataset was compiled independently and the model utilized rather simple, this result is expected.

A more refined dataset over a longer time period with a more complex model specification may have resulted in more robust findings but the methodology is valid and applicable. Regarding statistical testing, several hypotheses could be run on functional forms instead of the simple linear form utilized (a translog-cost function for example) but due to lack of price data this was not possible.

To summarize, this thesis estimated the cost efficiency of Finnish hospitals during 2011-2013 and how specialization affected their cost efficiency during the aforementioned time period. The mean cost efficiency was found to be 87% and specialization was found to lower the level of cost efficiency. The mean level of specialization of Finnish hospitals was found to be above zero yet not overly specialized at 0.66 (the most specialized hospital reached a value of 3.65). The results were estimated with a stochastic time-varying frontier analysis. The cost efficiency estimates are in line with previous findings from Finnish hospitals but contradict the findings with respect to the effect specialization has on cost efficiency. Therefore further research of interest would be to estimate cost efficiency of this dataset's hospitals with Lindlbauer and Schreyögg's (2014) new measures of specialization based on patient volumes instead of patient proportions. The comparative results would give important indicators of how sensitive this type of analysis truly is to the choice of specification and also how present economies of scale actually are in hospital performance. Another point of interest would be to gather time-series data on the operating costs of Finnish hospitals from the previous years and run these estimations on a longer panel to create a more reliable understanding of the evolution of the cost efficiencies of Finnish hospitals.

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ELECTRONIC SOURCES

THL 2015:

http://www.julkari.fi/handle/10024/134862

THL 2016:

http://www.julkari.fi/bitstream/handle/10024/136604/Tr20_18.pdf?sequence=6&isAllowed=y

STM:

https://stm.fi/sairaalat-erikoissairaanhoito?p_p_id=56_INSTANCE_7SjjYVdYeJHp&p_p_lifecycle=0&p_p_state=normal&p_p_mode=view&p_p_col_id=column-2&p_p_col_count=3&_56_INSTANCE_7SjjYVdYeJHp_languageId=en_US 29.08.2018

DATA

HOSPITAL COSTS FROM THL OPEN DATA SOURCE 2011-2015 USED AS A COMPONENT IN COMPILING THE DATA SET UTILIZED IN THIS THESIS:

https://thl.fi/fi/tilastot-ja-data/ohjeet-tietojen-toimittamiseen/sairaaloiden-toiminta-ja-tuottavuus/raportointi/tietokannat/tuottajatietokannat

The open source data used is called the hospital benchmarking time-series data. The data set includes benchmarking (performance-marking variabales) data over the past five years from hospitals in Finland. I utilized only the total operating costs corrected for inflation over the period 2011-2013 for hospital identifier code, hospital type, hospital district.

SOFTWARE

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