CHARLES UNIVERSITY

FACULTY OF SOCIAL SCIENCES

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Efficiency change in inpatient care provision under the DRG-based reimbursement mechanism in the Czech Republic

Master's thesis

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Year of defense: 2023

Declaration of Authorship

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Prague, May 3, 2023

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Abstract

Expenses on inpatient care form the largest share of Czech health expenditure, which raises concerns about its efficiency. Efficiency improvement belonged to one of the motivations for the implementation of reimbursement mechanism based on diagnosis-related groups, under which hospitals are paid a fixed amount per hospital case. This thesis contributes to the existing literature on DRG by assessing the changes in efficiency of inpatient care under DRG in the Czech Republic, focusing on the length of stay as a measure of resource utilization as well as an indicator of hospital efficiency. Furthermore, it contributes to this topic by using a unique and relatively large dataset containing patient-level information from 15 Czech hospitals over 2015-2019.

Employing models for count data, we observe the downward trend in length of stay over the examined period. This finding is in line with the intended effect of DRG. Moreover, the estimated result is robust when considering different subsamples – based on hospital size (large and medium-sized) or severity level of a patient. The only group where the decline in length of stay was not estimated were the most severely ill patients with major complications and comorbidities. Measured by the standard deviation of length of stay, the process of standardization of healthcare provision has also been observed. The results indicate enhanced hospital efficiency in terms of inpatient care when operating under DRG, which implies that hospitals can treat more patients using the same capacity.

JEL Classification	I10, I11, I15, I18, H51
Keywords	hospital care, length of stay, DRG reimbursement, Czech Republic
Title	Efficiency change in inpatient care provision under the DRG-based reimbursement mechanism in the Czech Republic

Abstrakt

Výdaje na lůžkovou péči tvoří největší část výdajů na zdravotní péči v České republice, což vede k diskusi o její efektivitě. Zlepšení efektivity patřilo k jednomu z motivů pro zavedení úhradového systému založeného na DRG, v rámci něhož je lůžková péče hrazena fixní částkou za hospitalizační případ. Tato práce obohacuje relativně omezenou literaturu zabývající se DRG a hospitalizační péčí - přináší analýzu změn efektivity v poskytování lůžkové péče po zavedení DRG v České republice. Konkrétně se zaměřuje na délku hospitalizace, což často slouží jako indikátor efektivity nemocnic. Dále k tomuto tématu přispívá využitím unikátního a poměrně rozsáhlého souboru pacientských dat z 15 českých nemocnic z let 2015-2019.

S využitím modelů pro diskrétní data byl ve zkoumaném období pozorován klesající trend délky hospitalizace, což se řadí mezi žádané efekty DRG. Odhadovaný výsledek je navíc robustní při zohlednění různých dílčích vzorků – na základě velikosti nemocnic (velké a střední) nebo úrovně závažnosti onemocnění pacienta. Jedinou skupinou, u které nebyl pozorován klesající trend délky hospitalizace, byli pacienti se závažnými komplikacemi a komorbiditami. Dále byl pozorován pokles směrodatné odchylky délky hospitalizace, který můžeme interpretovat jako probíhající standardizaci v poskytování lůžkové péče. Obě zjištění naznačují, že dochází k zefektivnění poskytování lůžkové péče, což má za následek, že nemocnice mohou léčit více pacientů při využití stejné kapacity a zdrojů.

Klasifikace JEL	I10, I11, I15, I18, H51
Klíčová slova	nemocniční péče, délka hospitalizace, úhradový mechanismus DRG, Česká republika
Název práce	Změna v efektivitě poskytování lůžkové péče v rámci úhradového mechanismu založeného na DRG v České republice

Acknowledgments

The author would like to express her gratitude especially to her supervisor PhDr. Lucie Bryndová for her support, comments and valuable advice. The author is also greatful to MUDr. Ing. Daniel Hodyc, Ph.D. for access to unique data set and for providing insights into medical aspects of the thesis, and to Mgr. Magdalena Škodová for other valuable insights into patient-level data.

This thesis is part of a project that has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 870245.

Typeset in LaTeXusing the IES Thesis Template.

Bibliographic Record

Jakubova, Barbora: *Efficiency change in inpatient care provision under the DRG-based reimbursement mechanism in the Czech Republic.* Master's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2023, pages 100. Advisor: PhDr. Lucie Bryndová

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Acronyms

ALOS Average length of stay

CC Complications and comorbidities

CZSO Czech Statistical Office

CZ-DRG Czech refined diagnosis-related group

DRG Diagnosis-related group

GDP Gross domestic product

ICU Intensive care unit

IQR Interquartile range

IR-DRG International refined diagnosis-related group

IRR Incidence rate ratio

LOS Length of stay

MCC Major complications and comorbidities

ME Marginal effects

NB Negative binomial

OECD Organisation for Economic Co-operation and Development

OLS Ordinary least squares

PTA Percutaneous transluminal angioplasty

PTCA Percutaneous transluminal coronary angioplasty

SHI Statutory health insurance

UZIS The Institute of Health Information and Statistics of the Czech Republic

WHO World Health Organization

ZT Zero-truncated

ZTNB Zero-truncated negative binomial

Master's Thesis Proposal

Author	Bc. Barbora Jakubová
Supervisor	PhDr. Lucie Bryndová
Proposed topic	Efficiency change in inpatient care provision under the DRG-based reimbursement mechanism in the Czech Republic

Motivation The diagnosis-related group (DRG) system belongs to reimbursement mechanisms by which hospitals are financed. It is primarily used for inpatient care, and it is based on the classification of patients into a limited number of DRG categories that should be clinically meaningful and relatively homogenous in terms of resource consumption patterns (Barouni et al., 2020). Each base is consequently associated with a specific cost weight and when multiplied by hospital's base rate, it determines the flat-rate payment (Boes & Napierala, 2021).

The DRG mechanism was widely implemented in many European countries -e.g., Switzerland, France, Germany, and also in the Czech Republic. Generally, several reasons for its introduction exist - the DRG system aims to decline the financial incentive to fee-for-service hospitals for keeping patients longer than necessary, to increase the transparency of hospital services as well as the efficiency of use of resources in hospitals (Barouni et al., 2020, Koné et al., 2018; Kotherová et al., 2021).

The effect of DRG implementation and the consequent reaction of hospitals are questioned by researchers and they are analysed from various points of view, various diagnoses are considered. For example, Geissler et. al. (2012) and Street et al. (2012) evaluate the appropriateness of the division of diagnosis-related groups in terms of costs and the length of stay. Or (2014) in the analysis of French DRG-system notes the need of balance between efficiency and quality of healthcare. Meta-analysis concerning German and Swiss studies claim the effect of the DRG system on the length of stay, rehospitalisation rate or changes in number of cases hospitalised (Koné et al. 2018).

In the Czech Republic, the DRG-based reimbursement mechanism started to be implemented in the 1990s, but more developed implementation came into force in 2007 and it was widely implemented in 2012 (The Health Systems and Policy Monitor, 2019). So far, only few studies focusing on the DRG system in the Czech environment exist. For instance, Nový (2016) measures its performance considering only one-year 2011. Kotherová et al. (2021) evaluate the DRG system's effects on the restricted sample of three hospitals. The assessment of the hospital behavioural changes under the DRG system concerning larger number of hospitals is still missing.

Hypotheses

Hypothesis #1: Hospitals significantly changed their behaviour and decreased resource utilization over time.

Hypothesis #1a: The length of stay (LOS) decreased significantly over time, mainly LOS in Intensive care unit.

Hypothesis #2: The size of behavioural changes differs among DRG bases, reflecting the development in individual medical fields.

Hypothesis #3: The development of use of resources varies among different types of hospitals.

Methodology The thesis will be based on data set with a multi-dimensional panel data structure, containing Czech hospital data, covering the period 2015-2019. The data will be grouped based on diagnosis-related groups, and individual (anonymized) hospitals will also be distinguished. I will work with two types of hospitals - university hospitals and regional hospitals, in total at least 15 hospitals will be analysed. The data set will be provided by and processed in cooperation with Advance Hospital Analytics.

The main variables of interest can be divided into three groups:

1. Length of stay - also distinguishing the stay in the intensive care unit
2. Laboratory and imaging techniques
3. Materials used - separately billed material (ZUM) and medicinal products (ZULP).

As the first step of my analysis, I will identify DRG bases that will be further studied, based on the literature review. Moreover, the selection criteria will be the number of cases registered under the given base, diagnoses which treatment covers stay in the intensive care unit, possibly cases belonging to Surgery and Internal medicine wards. In total, bases will be selected in the way to appropriately characterize the Czech IR-DRG system.

The main goal of the thesis is to analyse significance of changes over time. Thus, I will construct panel data model with the following baseline specification. The dependent variable will be the measure of hospitals' care provision, i.e., LOS, materials used or laboratory techniques. The independent variables will be time dummies capturing the possible effect. Other variables will be added to the model to control for other factors that might have affected hospitals' behaviour. For instance, health care capacities will be captured by the number of doctors per district, number of hospital beds per district or number of cases. Moreover, the information about average patient age and CC (complications & comorbidities) indicator will be also added as regressors.

The second aim is to determine if heterogeneity in hospitals' behaviour over time exists; to analyse if the development of hospitals' behaviour differs among but also within specific hospital groups. The second hypothesis will be addressed by dummy variables indicating hospital type. To be able to answer the third hypothesis, dummy variables indicating the type of DRG base will be also added to the model.

Expected Contribution As far as the author is concerned, any study concerning large number of hospitals and covering five years (2015-2019) does not exist in the Czech environment. The thesis will contribute by assessment of behavioural changes of Czech hospitals under the DRG reimbursement mechanism. Precisely, the thesis will assess whether hospitals have changed resource utilization over time.

Outline

1. Motivation: I will describe DRG-based reimbursement method of financing, its introduction and development in the Czech Republic. Knowing the context, I will introduce research question and explain hypotheses.

2. Studies on assessment of DRG: will summarize studies concerning the same topic, I will describe how the DRG system and hospitals' behaviour under DRG-based reimbursement was evaluated in studies conducted in other European countries – mainly Germany, Switzerland, France.

3. Data & Methods: I will describe the structure of data set and variables I will work with; I will also explain methods which will be used for the analysis.

4. Results: I will present results of the analysis.

5. Concluding remarks

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Chapter 1

Introduction

Health expenditure represents a non-negligible part of Czech national spending - in 2019, it represented 7.6% of the Czech GDP (WHO, 2023). Moreover, more than one quarter (26.8%) of health expenditure in 2019 was spent on inpatient care (CZSO, 2022b). In 2020, the first year of the COVID-19 pandemic, both indicators even increased to 9.2% and 29.9%, respectively. Since expenses on hospitals, especially on inpatient care, form one of the largest components of health expenditure, concerns about its efficiency arise.

The financing of Czech inpatient care has undergone broad development during the last decades. Specifically, diagnosis-related groups (DRG) were introduced and have been implemented as a reimbursement mechanism (Bryndová *et al.*, 2023). Under a DRG-based reimbursement mechanism, hospitals are reimbursed a fixed amount per hospital case based on its diagnosis. More precisely, hospital cases are classified into diagnosis-related groups that are clinically meaningful and relatively homogeneous in terms of resource utilization (Busse *et al.*, 2013). Each group is assigned a cost weight associated with the amount a hospital is reimbursed (Kotherová *et al.*, 2021).

The DRGs have been gradually introduced all over the world and also in the majority of European countries. It aimed to increase transparency and efficiency of inpatient care. Transparency can be achieved through patient classification, diagnosis coding, or measuring hospital output, while higher efficiency of resource utilization should be obtained by paying per number and type of cases treated. Combining these two features should also help to improve the quality of care or to foster competition between hospitals (Busse *et al.*, 2013; Boes & Napierala, 2021).

A relatively large number of researchers, especially foreign ones, evaluate the impact of the DRG system on healthcare provision. Besides its potential above-mentioned positive effects, they also scrutinize the unintended effects of DRG, such as increased readmission rate or mortality, cherry-picking, or decreased quality of care. Findings in the literature vary depending on the studied country or diagnosis. As an indicator of hospital efficiency, length of stay is usually analyzed. Given that all other factors remain unchanged, a shorter length of stay is associated with lower costs per inpatient case (OECD, 2023). Evaluating DRG, foreign literature concludes either negative (e.g., Schuetz *et al.*, 2011; Cheng *et al.*, 2012) or no effect on length of stay (e.g., Busato & von Below, 2010).

Only a limited number of studies were conducted in the Czech Republic dealing with inpatient care and the DRG system. The DRGs were implemented gradually in the Czech Republic, but a broader implementation came into force in 2012. However, little is still known about the changes in inpatient care provision when hospitals operate under the DRG classification. This thesis contributes to the current literature by exploring the development of hospital behavior under the DRG-based reimbursement mechanism and focuses on the length of stay. Specifically, the thesis uses patient-level data from 15 Czech hospitals between 2015 and 2019 to analyze two potential trends. Firstly, by employing models for count data – zero-truncated negative binomial and zero-truncated Poisson and by controlling for patient characteristics and other covariates, we investigate the time trend of length of stay with a hypothesis of decreasing length of stay under DRG, as hospitals gradually adapt healthcare provision to the reimbursement mechanism.

Secondly, with the standardized revenue per the same type of hospital case, the healthcare provided should be standardized as well. In other words, under DRG as well as under clinical pathways, which go hand in hand with the DRG-based mechanism, the treatment of cases within the same diagnosis should become standardized. Technically, the variance length of stay within the individual episodes of care and hospitals should decline. This hypothesis is addressed by examining the time trend of the standard deviation of length of stay.

Both hypotheses are further evaluated on different subsamples to analyze the robustness of potential time trends. Namely, they are analyzed separately for large and medium-sized hospitals; patients with different level of illness severity and also for five selected episodes of care.

Results reveal that length of stay gradually decreased in the examined period which indicates improvement in efficiency of inpatient care provision. The trend of length of stay is robust when distinguishing between individual subsamples. Slightly higher change was noted in case of medium-sized hospitals compared to large hospitals and also for patients without complications and comorbidities, while the downward trend was not observed only for group of cases with major complications and comorbidities. The decrease in length of stay is also observed for five selected episodes of care, however, its size differs across the episodes of care. Furthermore, the results revealed that length of stay variation within hospitals declined over time as well, indicating that hospitals have been standardizing inpatient care in terms of length of stay.

The rest of the thesis is structured as follows. Chapter 2 provides the context of the work, that is, literature review on the DRG-based reimbursement mechanism, Chapter 3 summarizes literature on inpatient length of stay and its modeling. Next, Chapter 4 extensively describes patient-level data and Chapter 5 explains the methodology used for the analysis. Chapter 6 describes and discusses the results of the conducted models. Lastly, Chapter 7 concludes the thesis.

Chapter 2

Literature review

In this chapter, the author will firstly briefly introduce the system of financing in the Czech healthcare sector and the types of reimbursement mechanisms in Section 2.1. Secondly, in Section 2.2, one of them - the diagnosis-related group (DRG) reimbursement mechanism will be described in more depth, followed by the explanation of development and key ideas of the Czech DRG systems in Section 2.3. Section 2.4 will review the literature concerning the effects of DRG on healthcare provision.

2.1 The system of financing in the healthcare sector in the Czech Republic

The Czech Republic has a statutory health insurance (SHI) system of financing, which requires citizens to be compulsory members of a health insurance fund. One can choose from seven available funds that exist in the Czech Republic in 2023. The SHI system is financed mainly through compulsory, wage based contributions administrated by the health insurance funds. These are accompanied by finance from general taxation and out of pocket payments. The monthly wage-based SHI contributions are paid for economically active people by employers, employees, and self-employed individuals; the state pays the contribution for economically inactive people (Bryndová *et al.*, 2023). SHI contributions are subsequently pooled and redistributed among insurance funds based on a risk adjustment scheme. Later, insurance funds pay for healthcare services provided to their members according to contracts made between the health insurance fund and the given healthcare provider. The general framework for the payment rules is also formulated in a Reimbursement Directive, published yearly by the Ministry of Health (Bertoli *et al.*, 2021). The payment mechanism depends on the type of healthcare provider and should aim to induce the providers to act efficiently (Kazungu *et al.*, 2018). Nowadays, the following reimbursement mechanisms are mainly combined within the Czech healthcare payment system: capped fee-for-service payments, activity-based prospective budgets and case payments based on DRGs (Bryndová *et al.*, 2023). The following subsections will briefly explain all mentioned reimbursement mechanisms but will mainly focus on the description of reimbursement mechanism based on the DRGs.

(Capped) fee-for-service payments

Capped fee-for-service scheme is applied for hospital outpatient services, ambulatory specialized services and selected procedures performed by general practitioners. The provider is paid for every reported rendered procedure until a certain limit or cap is met. Each procedure is priced by a certain number of points, which are published in the List of Health Services (MZČR, 2023a). The exact monetary value of one point is negotiated and yearly published in the Reimbursement Directive.

Capitation

The provider - a general practitioner - is paid for every registered patient per month. The capitation is risk-adjusted, the age and sex of a patient are taken into account - a higher index is assigned to children aged 0-4 years or seniors.

Activity-based prospective budgets & Case payments based on DRGs

These mechanisms are applied for inpatient care in acute care hospitals. In case of activity-based prospective budget, the provider - a hospital - is reimbursed a sum of money that is set in advance, related to a reference time period (last year) and considers the provider's production in the reference year (measured using DRGs). In case of case-based payments, a hospital is reimbursed predefined amount of money (defined via DRGs) for each hospitalized patient, based on patient's condition and other factors that might increase complexity or expected cost of their care.

2.2 Diagnosis-related group classification

As mentioned above, the reimbursement mechanism which is applied for hospital inpatient care is linked to the diagnosis-related group classification. The general idea of the system is that hospitals are reimbursed fixed amount per hospital case. More precisely, the diagnosis of a patient is allocated to one of the diagnosis-related groups; each group is connected with a relative weight that is consequently assigned to a given case. Summing relative weights of cases (that a hospital treats) gives a so-called case-mix. Subsequently, the reimbursement flat-rate payment for a hospital is calculated by multiplying the case mix by a hospital's base rate (Boes & Napierala, 2021).

The main reason for introducing the DRG payment mechanism in Europe is the effort to increase the quality of care, transparency, or to improve the efficiency of inpatient care (Böcking *et al.*, 2005; Busse *et al.*, 2013). The DRG system helps to improve efficiency by paying the fixed amount for the whole hospital case - the hospitals are thus incentivized to limit the services per patient and treat more patients (Busse *et al.*, 2013). In comparison, the previous hospital health systems were based on fee-for-service or global budget payments and provided different incentives. Fee-for-service incentivized the hospitals to provide as many services as possible and to extend the length of stay (LOS) for each patient, which might have led to inappropriate and unnecessary treatment. On the other hand, the global budget raised the risk of underproduction and not providing sufficient services (Busse *et al.*, 2013).

Transparency using the DRGs is achieved since it is based on documentation and coding – classifying a large number of individual patients into a limited number of clinically meaningful and relatively economically homogeneous categories. Such classification also enables the comparison of rendered services for each group across different hospitals, which is also known under the term "benchmarking" (Böcking *et al.*, 2005). For example, the assessment of source utilization can be conducted by comparing the proportion of cases in the individual DRGs – a higher proportion of cases in costly diagnosis-related groups means that a hospital treats more complex cases than another hospital. Likewise, the efficiency of care can be compared through the length of stay of patients belonging to the same DRG (longer stay means more costly treatment in one hospital than in another) (Busse *et al.*, 2013). An optimal interval of the length of stay is also stated for a given DRG group, meaning that lower LOS suggests incomplete healthcare provided, and prolonged LOS might be related to ineffective treatment (Chok *et al.*, 2018).

The concept of diagnosis-related groups was firstly formulated in the 1970s by researchers at Yale University. By defining "hospital product", they aimed to measure the activity of hospitals (Goldfield, 2010). The system's potential soon attracted policymakers in the United States, and it was first implemented as a payment mechanism for hospitals in 1983. Gradually, the DRG payment system was introduced worldwide in most industrialized countries, especially in Europe (Busse *et al.*, 2011).

Even though the principle of the DRG system is the same, each country accommodated it with respect to the local environment. Some countries firstly imported the system from abroad and gradually developed their own (Poland, Slovakia, the Czech Republic), and some developed their own system from the very beginning (Austria, England, the Netherlands). The Nordic countries have agreed on a common system. Despite the same general idea, the systems are quite heterogeneous and differ in, for example, the number of diagnosis-related groups, patient classification, and relative prices paid for a DRG (Busse *et al.*, 2013).

The following section describes the development of DRG in the Czech Republic and summarizes its main principles.

2.3 DRG system in the Czech Republic

The implementation of the DRG system in the Czech environment started to be prepared in the 1990s and should have accompanied various hospital reimbursement mechanisms of that time – fee-for-service, per diem payments and global budgets. The Czech Republic decided to choose the IR-DRG (International Refined DRG) system, which was based on a worldwide used AP-DRG (All Patient DRG) system. After years of testing, the IR-DRG was first officially used in the Czech Republic in 2007, but only a small fraction of inpatient services was included in the DRG system. Later, in 2012, the DRG became a dominating reimbursement mechanism in inpatient care (Alexa *et al.*, 2015).

In 2014, Czech policymakers decided that inpatient care would continue to be reimbursed using a reformed DRG system, since the original IR-DRG system did not appropriately reflect clinical reality and the associated costs. The new project "DRG Restart" has been launched in order to reform the DRG classification and DRG-weighting methodologies, to improve the granularity of reimbursement and thus to improve the system efficiency and to make it more transparent. After several years of development, evaluation and testing of the new DRG scheme known as CZ-DRG, the IR-DRG has been completely replaced by the new CZ-DRG system in 2021. Nevertheless, CZ-DRG is still developing up to now; version 5.0 has been in force in 2023, and a new version is in progress (UZIS, 2023a).

However, the role of DRG within the payment mechanisms differed over time. During the majority of time, DRG classification served rather as a performance measure used to determine the activity-based hospital's budget; while only small portion of inpatient care were subject to case-based DRG payments. With the introduction of CZ-DRG, the proportion of inpatient care reimbursed by DRG case payments grew, meaning that approximately 44% of inpatient care were subject to DRG case reimbursement in 2021 (Bryndová *et al.*, 2023).

2.3.1 Principles of IR-DRG

The methodology of IR-DRG has been formulated by the Definition Manual, which contained a set of algorithmic rules. Based on these rules, clinical cases are divided into a limited number of diagnosis-related groups, while the main emphasis is placed on the similarity of cases in each group as well as on the expense homogeneity of cases in each group. Hence, the result leads to a trade-off between highly homogeneous groups and the low number of groups (Hodyc, 2007).

Principle of categorization of hospital case is the following: firstly, the patient diagnosis is assigned to one of twenty-eight mutually exclusive Major Diagnostic Categories (MDC). The second level is a DRG base, which distinguishes whether the patient's treatment involves surgery. The last level is the diagnosis-related group, which divides the DRG bases into 3 groups based on patient's illness severity level - without complications or comorbidities (without CC), with complications or comorbidities (with CC), and with major complications or comorbidities (with MCC). Those DRG bases, for which the patient's severity level is not relevant, are not further split.

After the case categorization, a relative weight is assigned to the case. In case of DRG base payments, the reimbursement for the case is derived by multiplying the weight by the base rate. Relative weight expresses the relation of average expenses among DRG groups and indicates the relative resource intensity of all patients included in a group. Relative weight equal to one corresponds to a patient with average expenses. Relative weight greater than one is equal to a medically more complex and financially more costly patient - the opposite holds for a relative weight smaller than one (Matušek, 2011).

Additional criterion is taken into account when assigning the relative weight to a case. In order to assign a respective relative weight to a case, the case's length of stay should fit into a predefined interval, bounded by a low trim point and a high trim point. If the case's LOS is below the low trim point or above the high trim point, the relative weight is accommodated. Relative weights, base rate, the average length of stay and trim points are yearly published in Reimbursement Directive, and might be subject to annual changes.

Summing all relative weights of a certain group of cases (e.g., all cases treated in a hospital within a year) forms a case-mix. Case-mix expresses the total medical and financial intensity of the group of cases. Dividing the case-mix by the number of cases gives the case-mix index, enabling the comparison of hospitals in terms of complexity of treated cases and the proportion of such cases (Kožený *et al.*, 2010).

2.3.2 CZ-DRG changes

In comparison to IR-DRG, CZ-DRG, which has been currently in place in the Czech Republic, differs in several aspects. For instance, it restructured the hierarchy of coding, and it also contains approximately two times more classification bases (727 vs. 373) and 1.5 times more DRG groups (1784 vs. 1057). In addition, it introduces a new methodology for the calculation of severity of a hospital case, where more degrees of severity are implemented. Finally, more parameters for classifications into DRG bases and groups were introduced. Examples of parameters that are evaluated during the classification are gender and age of a patient, weight of the new-born, principal and secondary diagnoses, the expertise of the inpatient admission ward, etc. The current system is described on the website of the Institute of the Health Information and Statistics of the Czech Republic (UZIS, 2023b).

2.4 Evaluation of DRG-based reimbursement mechanism

As already mentioned, the main goal of the DRG implementation in the majority of countries was to increase the quality of care, efficiency, and transparency.

However, the real DRG impacts are still being investigated and are the subjects of analysis by many researchers all over the world. The DRG systems have been assessed from various perspectives. In his meta-analysis, Böcking *et al.* (2005) formed five groups of measures of the DRG mechanism, which were considered most often in other studies: "*(1) cost and profitability, (2) length of stay and treated cases, (3) coding, (4) patient selection and referrals, and (5) quality of care and treatment intensity*".

The plausible effects noted in literature are reduced hospital costs (Böcking *et al.*, 2005), greater funding and spending transparency, decreased length of stay, improved efficiency, and shorter waiting times (Palmer *et al.*, 2014).

Contrarily, the DRG mechanism might have brought unintended changes in the behavior of healthcare providers. For instance, researchers have investigated potential lower quality of care (Fässler *et al.*, 2015), inadequate and premature discharges or increased rehospitalization rate (Barouni *et al.*, 2021; Palmer *et al.*, 2014), the effect on mortality rate (Kutz *et al.*, 2019) or upcoding – manipulating the coding on patients to assign patients to a DRG associated with higher reimbursement (Milcent, 2021).

Since each country cultivates the system in different time and environment, the author further decided to group studies by studied country with a focus on German G-DRG and Swiss DRG (that was developed from G-DRG). Recent literature offers many studies, including also meta-analyses, concerning these two countries. Besides, when designing Czech CZ-DRG, G-DRG served as an inspiration.

2.4.1 Case of Germany

Summarizing studies, which evaluate the German DRG system, Herwartz & Strumann (2014) conclude no significant improvement occurred in the overall hospital efficiency after implementing the DRG. Another examination found out that the quality of care was either not impacted or improved. On the other hand, Koné *et al.* (2019) mention in their meta-analysis that most of the reviewed studies pertaining to German DRG system found a significant drop in length of stay under DRG. Moreover, Busse *et al.* (2011) summarize that no adverse effects of the DRG were found to be present, precisely cream-skimming or inappropriate early discharge.

2.4.2 Case of Switzerland

Many studies focusing on the DRG reimbursement mechanism in Switzerland can be found. Before nationwide implementation of DRG in 2012, some cantons have already implemented it. Such situation has allowed the researchers to compare the functionality of DRG with other payment systems (fee-for-service per diem) within one country (e.g., Busato & von Below, 2010; Kutz *et al.*, 2019; Schuetz *et al.*, 2011).

Summarizing the noted effects of the Swiss DRG, Schuetz *et al.* (2011) estimated that length of stay in hospitals with DRG financing is shorter by 20% in comparison to fee-for-service hospitals, however, without apparent harmful effects on patient outcomes and quality of life measures. In the study of intensive care units in Zurich hospital, Chok *et al.* (2018) did not find a significant difference in length of stay before and after DRG implementation. Boes & Napierala (2021) point out the short-term negative effect of DRG on hospital performance in case of hospitals that have previously operated under the per diem reimbursement. Further, these researchers also conclude that hospitals, that had already worked under DRG before, have adapted to the official DRG implementation more quickly and efficiently. Kutz *et al.* (2019) and Busato & von Below (2010) report an increased re-admission rate, while Thommen *et al.* (2014) observe no change in re-hospitalization. Another finding is the decreased in-hospital mortality (Kutz *et al.*, 2019), but no effect on intensive care unit mortality has been observed (Chok *et al.*, 2018). Thommen *et al.* (2014) note the unproblematic introduction of the system in terms of patients' satisfaction. Similarly, according to Fässler *et al.* (2015), the quality of patient care and physicians' job satisfaction was rated as good.

2.4.3 Evaluation of DRG design

Besides the measure of resource utilization and quality of care, some studies also deal with the design of DRG and with the extent to which it captures the variability of costs of the hospitalized. In other words, they study whether the cases assigned to DRG groups are homogeneous enough in terms of costs (or the length of stay), since the homogeneity of the groups has a consequent impact on reimbursement amount per hospitalized case (hospital revenues).

Researchers within the "Euro DRG" project aimed to compare the ability of the DRG systems in ten countries across Europe to categorize patients into resource homogeneous groups (measured by patient costs or patient length of stay). Analyzing 10 episodes of care (e.g., hip and knee replacement, childbirth, cholecystectomy, ...) separately, it has been found that patient characteristics and treatment variables explain resource variation better than DRG for hip replacement (Geissler *et al.*, 2012) or acute myocardial infarction (Häkkinen *et al.*, 2012). When concerning also other episodes of care, researchers doubt whether European systems rely on the most appropriate classification variables and suggest refinement of DRG systems by inclusion of patient-specific as well as treatment-specific variables (Häkkinen *et al.*, 2012; Bellanger *et al.*, 2013; Mason *et al.*, 2012). However, based on the researchers' conclusions, there seem to be more variability between individual episodes of care than between European DRG systems (Tan *et al.*, 2013).

2.4.4 Existing literature on DRG in the Czech Republic

As far as the author is concerned, not many studies concerning the assessment or the impacts of the DRGs on the Czech inpatient care have been conducted. Since CZ-DRG has been in force relatively shortly, all studies that are mentioned below deal with IR-DRG classification.

The most recent study by Kotherová *et al.* (2021) evaluated the impacts of the DRG system on Czech hospital financing. Using data from three regional hospitals covering the period of 2012-2018 and conducting a cost-revenue analysis completed by interviews with DRG experts, the researchers conclude that the setup of the IR-DRG system does not incentivize major positive changes (predictability of payment for hospital cases, transparent financing, or efficiency) and suggest changes that might improve the system. Similarly, Dolejšová (2019) also highlighted the need for the cultivation of the DRG system to design the reimbursement scheme adequately to the real hospital costs. Nový (2016) measured the performance of the Czech DRG classification system in terms of ability of the system to explain the variation in length of stay. The study of individual-level data from the year 2011 indicates a decent performance of the IR-DRG system, but with a need of optimization.

Regarding hospital efficiency, studies of Votápková *et al.* (2013) and Mastromarco *et al.* (2019) provide supporting evidence that the DRGs may serve as an efficient reimbursement mechanism for inpatient care. Besides, Votápková (2020) compares the two studies and notes that hospital efficiency may increase when DRGs are implemented as performance measure and reimbursement mechanism.

Our study contributes to the current Czech literature on DRG by assessing the development of inpatient care provision under DRG-based reimbursement mechanism over time, focusing on length of stay as a measure of resource utilization and hospital efficiency. Furthermore, it contributes to this topic by using a quite large dataset containing patient-level information from 15 Czech hospitals over 2015-2019.

Chapter 3

Recent research on length of stay

As mentioned before, this thesis evaluates the changes in efficiency of inpatient care measured by length of stay (LOS) and using patient-level data. Hence, the author has decided to dedicate the following chapter to summarizing current literature analyzing inpatient length of stay, first, from the general context in Section 3.1, then from more technical perspective – how LOS is modeled using patient-level data in existing literature, in Section 3.2.

3.1 Length of stay as a variable of interest

In their studies, the researchers are often focusing on length of stay, since together with cost, it is considered as a measure of hospital resource utilization and as an indicator of the efficiency of the hospital delivery (van de Vijsel *et al.*, 2015). Even though cost-variation analysis better reflects the reality and thus, it is preferred for studies of resource usage, cost data at granular (patient) level are often not available. An advantage of length of stay is the straightforward way in which it is defined and hence, better accessibility on the patient level (Street *et al.*, 2012).

As already noted, when analyzing the impacts of DRG on healthcare systems, LOS is often considered as one of the criteria. Researchers either assess the direct impact of DRG on LOS (for instance, Louis *et al.*, 1999; Cheng *et al.*, 2012; Schuetz *et al.*, 2011) or they evaluate the DRG systems based on their ability of explanation of LOS variation (Street *et al.*, 2012; Häkkinen *et al.*, 2012). Worth noting is the approach of Boes & Napierala (2021), who modified LOS to LOSC (the length of stay weighted by benchmark value), arguing that LOSC serves as a suitable measure for comparison of hospital performance while also eliminating time trends.

Apart from studies connected with the assessment of DRG, length of stay is also considered for other research questions – for instance, modeling of LOS outliers – patients with extremely short or long LOS, and how to detect them (Freitas *et al.*, 2012; Lin *et al.*, 2022; Felder, 2009). Another aim is to predict inpatient LOS in order to achieve better coordination of healthcare services – and prevent from the inefficient extension of LOS (e.g., Kiss *et al.*, 2021; Stone *et al.*, 2022; Aghajani & Kargari, 2016).

Only a few studies investigate the development of LOS variation within and between hospitals. However, as van de Vijsel *et al.* (2015) argue, this kind of analysis is important for scientific as well as for policy-making purposes - observing decline and stabilization of LOS variation might imply that further improvements in efficiency are limited, while the opposite might hold for increase in LOS variation. The study of van de Vijsel *et al.* (2015) is one of the few that deals with the LOS variation over time and the first study that investigates within and between hospital variation in case of Dutch hospitals between 1995 and 2010. Via linear-mixed models, the authors have found that trends in LOS variations differ between procedures, but they see room for further LOS reduction for all of them; within-hospital variance has been estimated to be much greater than between-hospital variance.

Many studies deal with various factors that might affect the length of stay. For example, Thomas *et al.* (2016) scrutinized the effect of malnutrition on LOS, or Earnest *et al.* (2006) investigated the relationship between LOS and time of admission. Even if the explanation of LOS variation is not the main research question, researchers control for factors that might influence LOS. Most frequently used factors are related to hospital characteristics, patient characteristics, patient clinical data or treatment methods – examples of such factors are summarized in Subsection 3.2.1 and Subsection 3.2.2.

3.2 Length of stay modeling in literature

Various approaches to the analysis of LOS using patient-level or administrative data can be found in literature, depending on the study purpose. Some studies adopt direct hypothesis testing using statistical tests (e.g., Louis *et al.*, 1999). The direct impact of DRG on length of stay is usually estimated using a difference-in-differences model (Boes & Napierala, 2021; Cheng *et al.*, 2012; Farrar *et al.*, 2009); Schuetz *et al.* (2011) utilized multivariate adjusted Cox models. Probit or logit models are employed, for example, in studies that deal with LOS outliers (Freitas *et al.*, 2012; Liu *et al.*, 2010). Data mining techniques are also innovatively used for predicting LOS (Aghajani & Kargari, 2016).

Regarding LOS variation in terms of hospital and patient characteristics or treatment methods, either OLS, alternatively OLS with log transformation (Tan *et al.*, 2013; Earnest *et al.*, 2006; Achanta *et al.*, 2019), or count data models are chosen. Concerning the count data models, the Poisson or negative binomial versions of the model appear to be among the most frequent approaches used in the previous literature (Wolff *et al.*, 2015; Carter & Potts, 2014; Epstein *et al.*, 2010).

In order to combine patient and hospital characteristics, a two-stage model could be utilized. This methodology served for evaluation of the DRG systems in Europe within the project EuroDRG. The authors suggest a two-stage model - in the first stage, they analyze the effect of patient characteristics on LOS using unconditional Poisson or negative binomial regression. The authors use variables such as the type of DRG group, patient characteristics and dummy variables capturing the "fixed effects" of hospitals. In the second stage, the estimated hospital effects are regressed on hospital characteristics to explain the LOS variation between hospitals (Street *et al.*, 2012).

3.2.1 Hospital characteristics

Regarding the examples of hospital characteristics and their effects that are discussed in the literature, frequently mentioned variables are hospital size, number of beds, number of doctors, hospital ownership, type of financing and teaching status (Tan *et al.*, 2013; Street *et al.*, 2012; Freitas *et al.*, 2012).

An empirical example might be the study of Yuan *et al.* (2000), who focused on the association between hospital types and the length of stay, finding out that not-for-profit teaching hospitals had a relatively longer LOS compared to patients at different hospital types. The offered explanation is the medical education and research activities that are conducted at teaching hospitals. However, the authors conclude that these hospitals overall perform better in terms of mortality. Another study conducted by Freitas *et al.* (2012), which analyze the proportion of LOS outliers, concludes that large teaching hospitals have significantly more outliers than other hospitals.

3.2.2 Patient-level characteristics

Employing patient characteristics is dependent on the source data and the extent of information about hospital cases that is available to researchers (Stone *et al.*, 2022). Patient-level characteristics are usually a mixture of sociodemographic variables and other clinical data.

The most frequently included patient characteristics are age and gender of a patient (used by e.g., Street *et al.*, 2012; Epstein *et al.*, 2010; Schuetz *et al.*, 2011; Wolff *et al.*, 2015). Sometimes, the dataset also allows the researchers to control for insurance class (Boes & Napierala, 2021), nationality – immigration, income, education level (van de Vijsel *et al.*, 2015) or distance from patient residence to the hospital (Freitas *et al.*, 2012).

From the information about treatment, researchers often include information about the severity of hospital case and the level of treatment complexity. Street *et al.* (2012) or van de Vijsel *et al.* (2015) used Charlson index to create severity levels. Geissler *et al.* (2012) considered the number of procedures and patient's diagnosis. Primary and secondary diagnoses were captured by Boes & Napierala (2021). Tan *et al.* (2013) controlled for case's emergency and admission at the intensive care unit.

Data on patient admission and discharge are also often available – in addition to emergency admission, Geissler *et al.* (2012) also considered the type of transfer in and transfer out. Further, Freitas *et al.* (2012) took the patient decease into account. The time of admission has been a concern of Earnest *et al.* (2006), who investigated not only the effect of the day of week but also considered weekends, public holidays, and the exact time of admission.

Other clinical data contains information, for instance, about complications such as urinary tract infection, wound infection (Street *et al.*, 2012), laboratory values (Achanta *et al.*, 2019) or other clinical findings – body temperature, heart rate, etc. (Schuetz *et al.*, 2011). Some variables are procedure-specific – the study of hip replacement LOS controls for the reason of replacement – fracture, partial or revision (Geissler *et al.*, 2012). Number of stents was incorporated into the model for acute myocardial infection (Häkkinen *et al.*, 2012). In case of cholecystectomy, van de Vijsel *et al.* (2015) distinguished between the ways the procedure has been carried out – laparoscopic procedure or open.

3.2.3 Selection criteria of patient-level data used in literature

When dealing with patient-level data, researchers often provide information on data cleaning as well as on the selection criteria for hospital cases that are included in the final datasets that are further analyzed.

The main concerns are usually how to treat outliers, however, a universal technique how to detect them does not exist. Various factors should be considered when choosing the appropriate methodological approach, especially the purpose of the analysis (Freitas *et al.*, 2012). The literature offers multiple approaches how to deal with extreme values (inpatient days) in the dataset. For instance, Street *et al.* (2012) considered hospitalizations with LOS at least three times higher than the standard deviation of LOS as outliers and discarded them. Lee *et al.* (2003) defined the extreme outliers as cases with LOS at least three times higher than the average length of stay. Freitas *et al.* (2012) used the trim point defined by the geometric mean plus two times standard deviations. Pirson *et al.* (2013) determined outliers using the interquartile range (IQR) approach. Lin *et al.* (2022) compared some of the above-mentioned techniques and proposed a new one, which is based on lognormal distribution. Some studies define exact threshold for outliers – for instance, 365 days (Verburg *et al.*, 2014) or 65 days (Dismuke & Sena, 1999).

Besides outliers, another criterion that often appears in the literature is age - for example, Tan *et al.* (2013) or Street *et al.* (2012) excluded patients that are less than one year old – due to only few cases and different treatment procedures. Schuetz *et al.* (2011) chose to focus on adult patients (patients older than 18 years).

Another criterion is, for instance, the type of discharge – early discharges and decease are omitted (Verburg *et al.*, 2014; Earnest *et al.*, 2006) or treated separately (Dismuke & Sena, 1999). Some criteria are specific to the episode of care – for example, Tan *et al.* (2013) excluded male patients in case of the breast cancer.

Chapter 4

Data

This chapter introduces and describes the dataset used for the analysis of the development of inpatient length of stay under DRG in Czech hospitals. First, the data are presented from the general perspective - its origin, selection of episodes of care as well as data coverage. Subsequently, the data cleaning process is explained and lastly, the final dataset is introduced. The last section, Section 4.5, is dedicated to descriptive statistics that starts with the analysis from a broad context and combines also publicly available data, then it continues with the description of data used for the analysis.

4.1 Data selection

The analysis in this thesis is based on the de-identified patient-level data, which form multidimensional panel data (time, episode of care, hospital). The data were provided by Advance Hospital Analytics, a company that focuses, among other things, on analyzing hospital data in terms of expenses and resource utilization. This type of data is usually used for benchmarking - the comparison of one hospital with a benchmark value calculated from the rest of hospitals. The data were processed by the author under the company's supervision.

Dataset consists of patient-level data from 15 Czech public acute care hospitals covering the period 2015-2019. Hence, the data cover the period when the hospital cases were classified via IR-DRG. Hospitals can be divided either by type - 8 university (teaching) and 7 regional hospitals, or by size - 8 large and 7 medium-sized hospitals. For defining the size categories, we use the criteria of the number of hospitalizations per year and number of beds in the hospital. Thresholds were defined based on expert consultations - large hospitals have more than 1,000 hospital beds and treat more than 40,000 patients a year; the opposite holds for medium-sized hospitals. In addition, the first criterion has also been used in previous literature, namely by Freitas *et al.* (2012) for grouping Portuguese hospitals. The list of hospitals considered for our analysis is presented in Table 4.1. Due to data protection, from now on, hospitals will be presented only in an anonymized form if it is necessary.

Table 4.1: Hospitals considered for the analysis

Hospital	**Type**	**Size type**
FN Brno	university	large
FN Královské Vinohrady	university	large
FN Motol	university	large
FN Olomouc	university	large
FN Ostrava	university	large
FN Plzeň	university	large
FN u sv. Anny v Brně	university	medium-sized
Všeobecná fakultní nemocnice v Praze	university	large
Nemocnice Jihlava	regional	medium-sized
Krajská nemocnice Liberec	regional	medium-sized
Nemocnice Karlovy Vary	regional	medium-sized
Oblastní nemocnice Mladá Boleslav	regional	medium-sized
Nemocnice České Budějovice	regional	large
Nemocnice Pardubice	regional	medium-sized
Krajská nemocnice Tomáše Bati	regional	medium-sized

Note: large $\sim$ hospital with more than 40,000 hospitalizations per year and more than 1,000 hospital beds
Source: Author's compilation

In total, the information about approximately 708,000 hospital cases is available to the author. Cases were selected from the original sample of all hospital cases treated in the selected hospitals over the observed period in a way to include a wide range of medical surgical procedures. Furthermore, cases were grouped into 34 episodes of care based on the medical procedure that was rendered and reported at a case. The reason why the analysis did not stick to IR-DRG grouping, which was in place when our data were collected, is that

DRG bases in IR-DRG were not homogeneous enough to analyze the changes in length of stay.

An illustrative example might be the case of total replacement of hip and total joint replacement in the upper extremity. In IR-DRG, these cases belonged to one DRG base - 0804. However, each of these episodes of care has a different complexity of treatment and consequently, they differ in the use of resources. The average length of stay (ALOS) for total hip replacement is approximately 7.8 days, whereas the average length of stay of total joint replacement in the upper extremity is around 11 days. Thus, if we analyzed changes within this DRG base over time, the analyses would be biased by the proportion of cases per each episode of care within the base, and it might give us biased findings. To prevent this, the two procedures are group into two separate episodes of care.

In addition, episodes of care are defined by a group of medical procedures that correspond to specific DRG bases and represent the key medical procedures in specific DRG bases within the new CZ-DRG classification. Other selection criteria for episodes of care and medical procedures were the number of cases and the availability of data about those procedures within 5 years (2015-2019). Moreover, different surgical methods were categorized separately (for instance, open and laparoscopic cholecystectomy) to distinguish between the intensity of procedures which may also influence the use of resources and patient length of stay. Table 4.2 presents the selected episodes of care, which were grouped based on clinical areas for clarity. Medical procedures defining each episode of care as well as Czech names of episodes of care are enclosed in Appendix (Table A.1).

Table 4.2: Episodes of care selected for the analysis

Clinical area	**Episode of care**
Surgery	Breast resection, Bowel resection, Laparoscopic cholecystectomy, Open cholecystectomy, Closure of defect with a skin flap, Gastrectomy, Anatomical lung resection, Extra-anatomical lung resection, Tonsillectomy, Thyroidectomy, Parathyroid tumor removal
Surgery - hernias	Hernia - children under 3 years, Hernia - children 3-15 years, Hernia - adults

Continuation of Table 4.2

Clinical area	Episode of care
Cardiac surgery	Aortic valve procedures, Aortocoronary bypass surgery, Valve replacement
Invasive cardiology	Catheter ablation - complex, Cardioverter - defibrillator implantation, Pacemaker implantation, PTA, PTCA
Vascular surgery	Endarterectomy, Superficial limb vein surgery
Orthopedics	Total joint replacement in the upper extremity, Total hip replacement, Total knee replacement, Complex arthroscopy, Reconstructive arthroscopy
Urology	Nephrectomy, Transurethral prostatectomy, Transurethral resection of bladder tumor
Delivery	Vaginal delivery, Cesarean section

Source: Author's compilation

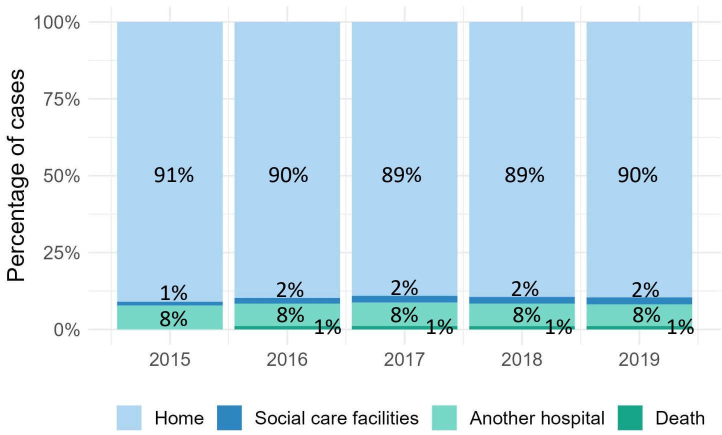
4.2 Cleaning the patient-level data

As mentioned above, we decided to group the medical procedures into several episodes of care. Since multiple medical procedures are connected to one episode of care, and more than one procedure is usually recorded at one hospital case, we face the problem of duplicate hospital cases in a dataset. Having a hospital case more than once is not desirable since it can lead to biased findings, as in such case, the only variable that differs is the type of procedure, while the rest of the information about the hospital case is the same. Generally, various analyses and calculations (e.g., average) would give higher weight to the case that is recorded more than once in a group. Therefore, each patient was left in the dataset only once. An adjustment has also been made in the case of interconnected episodes of care and patients that appeared in both groups, namely in laparoscopic cholecystectomy and open cholecystectomy, anatomical lung resection and extra-anatomical lung resection, or vaginal delivery and cesarean section. For some hospital cases, where multiple procedures were recorded, the case was assigned to both related episodes of care. Possibly, the patient was treated using one approach, but then he/she had to be switched to the second one. Having the case in both groups might also give biased findings because LOS is noted for the whole hospital case, and one episode of care from the pair is usually less resource-demanding than the other. However, if the patient also stayed in the less demanding episode of care, it would cause an upward bias in terms of the length of stay for the given episode of care. Hence, the cases that had recorded both laparoscopic cholecystectomy and open cholecystectomy were left only in open cholecystectomy. In the case of lung resection, patients were left in open lung resection. In the last case, vaginal delivery and cesarean section, patients were assigned only to cesarean section episode of care.

Censored length of stay

The next step of data cleaning was subtracting censored hospital cases, i.e., patients that died during the hospitalization or were discharged earlier or discharged to another hospital. Such data is considered censored since it does not give us information about the true LOS if the hospitalization had standard progress. The Figure 4.1 illustrates the proportion of censored cases in the data grouped by years; censored cases consistently represent approximately 8% of all cases each year (marked as Another hospital and Death on the graph). Hence, removing such cases would equally affect the number of cases each year.

Figure 4.1: Hospitalizations by type of discharge



Source: Author's compilation

Trimming of outliers

In the next step of the data cleansing, we decided to omit cases with too long length of stay (high outliers), which is also a frequent approach in the existing literature, as it was discussed in Subsection 3.2.3. In order to identify such cases, we used the definition through IQR and extreme outlier, which is defined as a value greater or equal to third quartile (Q_3) plus three times interquartile range ($Q_1 - Q_3$) :

$$\textit{high outlier} = \{x | x \geq Q_3(x) + 3 \cdot (Q_3(x) - Q_1(x))\}. \tag{4.1}$$

Extreme cases are not considered in the analysis because even though they have appropriate medical procedures to be categorized in one of the defined episodes of care, there might be another more serious reason for their hospitalization that we are not able to control for using our data. Moreover, we discarded only the extreme outliers, as in one part of the analysis, we are interested in the development of variance in LOS. If we chose a stricter rule for the identification of outliers, we would lose the variance in data that we would like to investigate. Applying this methodology for each episode of care in each year separately, 3.8% of cases from the total sample have been determined as extreme outliers.

After the previous step of the data cleansing process, further inspections regarding possible administration errors were carried out - for example, we discarded male patients from vaginal delivery and cesarean section episodes of care. After the whole data cleansing process, our final data set used for the analysis consists of approximately 537,000 observations.

4.3 Data coverage

Before moving to the description of variables, it is worth estimating the coverage of our data, i.e., how large our sample is compared to the population - all hospital cases in the Czech Republic. At the general level, there were 194 hospitals in the Czech Republic in 2019, while our data contains hospital cases from 15 hospitals, which accounts for 7.7% of the total number of hospitals. However, in terms of university hospitals, we analyze data from 8 out of 12 Czech university hospitals.

Regarding hospital cases, 1.9 million of hospital cases were treated in Czech acute care hospitals in 2019 (CZSO, 2022a). Our sample includes data about 125,980 cases treated in 2019, which stands for approximately 6.5% of all hospitalizations in the Czech Republic in that year.

Moving further to the individual episodes of care, we are able to estimate the coverage of our sample within episodes of care by linking it with the CZ-DRG base or group, for which we have available the total numbers of hospital cases in 2019 (information was provided by Advance Hospital Analytics). Based on this approach and considering only the selected episodes of care, our data cover approximately 30-40% of all relevant hospital cases treated in 2019 in the Czech Republic. However, the coverage varies across episodes of care.

4.4 Patient characteristics

The analyzed patient-level data provide us with information on all individual cases that were recorded in the selected hospitals during the selected time period 2015-2019. One observation represents one medical procedure recorded to a hospital case. Thus, one observation captures information about the type of procedure, the anonymized identification number of hospital case, the date on which the procedure was conducted, and additional information about the hospital case, for instance, the date of admission, the date of discharge, length of stay at intensive care unit, the type of discharge, gender, age, and the DRG structure which the case follows. A more detailed description of variables that will be included in the analysis can be seen in the following Table 4.3, summary statistics of categorical variables is included in Appendix (Table A.2,A.3).

Table 4.3: Patient-level data: Variables overview

Variable	**Description**	**Values**
Length of stay (LOS)	Inpatient length of stay measured in days and calculated as the date of discharge minus the date of admission plus one	*Mean: 5.86* *Median: 5.0* *St. dev.: 4.09* *Min: 1.0* *Max: 72.0*
Intensive care unit length of stay (LOS - ICU)	The number of days a patient stayed in the intensive care unit	*Mean: 0.75* *Median: 0.0* *St. dev.: 2.10* *Min: 0.0* *Max: 67.0*

Continuation of Table 4.3

Variable	**Description**	**Values**
Year of discharge (Year)	Year in which a patient was discharged, which is considered as the year to which the hospital case is categorized	*year 2015* - *year 2019*
Age group	Age of patient, recorded as decennium, thus it is a categorical variable. For example, patients belonging to category *DEC 02* are from 10 to 19 years old	*DEC 01* - *DEC 10*
Gender	Categorical variable indicating if a patient is a male or a female	*male* *female*
Complications and comorbidities (CC)	Variable serving as a proxy for the severity of hospital case, derived from IR-DRG classification	*without CC* *with CC* *with MCC* *without split*
Type of discharge	Categorical variable capturing the type of discharge	*home* *social care facil.*
Hospital	Hospital where a patient was hospitalized	See Table 4.1
Episode of care	A group of procedures to which a patient belongs based on the rendered procedure	See Table 4.2

Note: social care facil. = social care facilities

4.5 Descriptive statistics

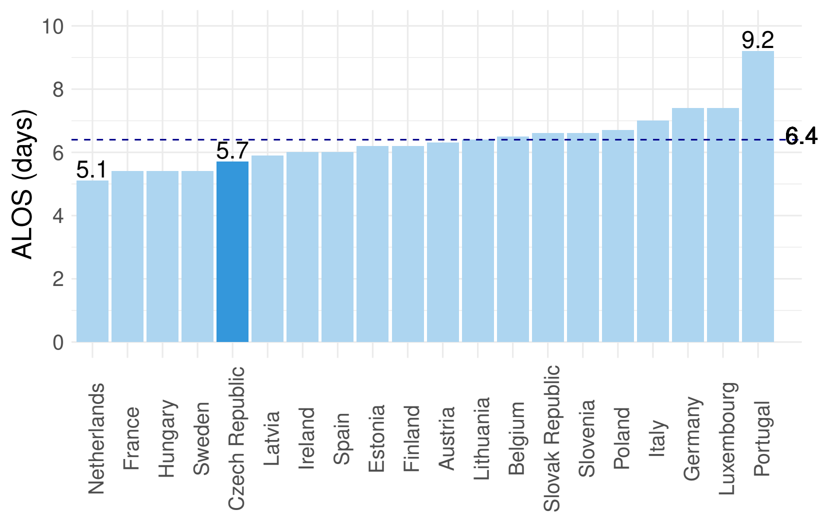
In this section, the descriptive statistics of our data will be presented and discussed. Moreover, the data will be put into a broader context. Firstly, the Czech Republic will be compared with other European countries. Subsequently, our data sample will be compared with the general data collected by the Czech

Statistical Office (CZSO) and the Institute of Health Information and Statistics of the Czech Republic (UZIS).

European context

Starting with the comparison at the European level, the Figure 4.2 below compares the average length of stay (ALOS) in selected European countries in 2019 using data from OECD (2023), where only acute cases are considered. The dashed line depicts the average of European countries. The average length of hospital stay in the Czech Republic in 2019 was 5.7 days, which is fairly below the European average (6.4 days), ALOS is lower only in 4 out of 20 displayed countries. The Netherlands reports the lowest average length of stay of 5.1 days; in comparison, Portugal has the highest ALOS of 9.2 days.

Figure 4.2: Average length of stay in OECD countries (2019)



Source: OECD (2023)

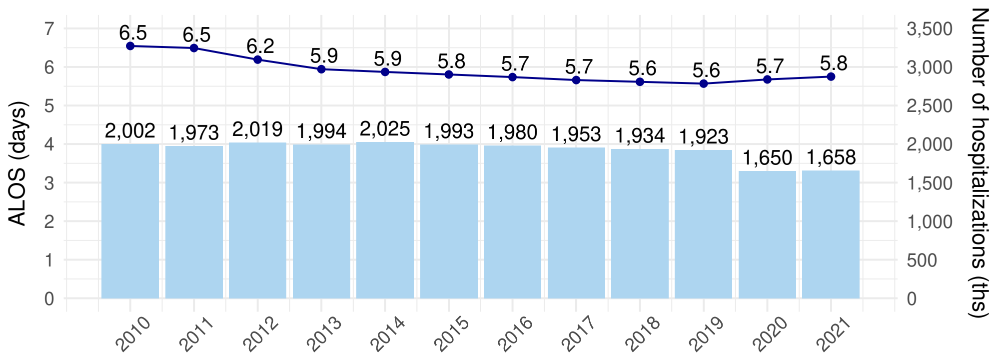
Length of hospital stay in the Czech Republic

According to data available at CZSO (2022a), LOS in Czech acute care hospitals has decreased over the last decade. In 2010, the ALOS was 6.5 days. Since then, the ALOS has declined by 0.7 days. The development is depicted in the Figure 4.3.

During the 5 years (2015-2019) that are also captured in our data, we can observe a gradual decrease in ALOS by 0.2 days. The last two years, for which data are available at CZSO (2022a), were marked by the COVID-19 pandemic. In these years, the ALOS slightly grew compared to the last pre-pandemic year 2019, precisely by 0.1 days in 2020 and by 0.2 days in 2021.

Nevertheless, the effect of the COVID-19 pandemic is more evident in the number of hospitalizations, the development of which is also displayed in the Figure 4.3. While the number of hospitalizations fluctuated moderately from 2010 to 2014 and slowly decreased from 2014 to 2019, it experienced a significant drop in the pandemic years 2020 and 2021, when the number of hospitalizations declined by approximately 400,000. This trend reflects the restrictions of non-emergency and planned hospitalizations that hospitals had to postpone to ensure sufficient capacity (hospital beds and medical staff) for the treatment of patients suffering from COVID-19 (Přádová, 2021).

Figure 4.3: Hospitalizations in Czech acute care hospitals

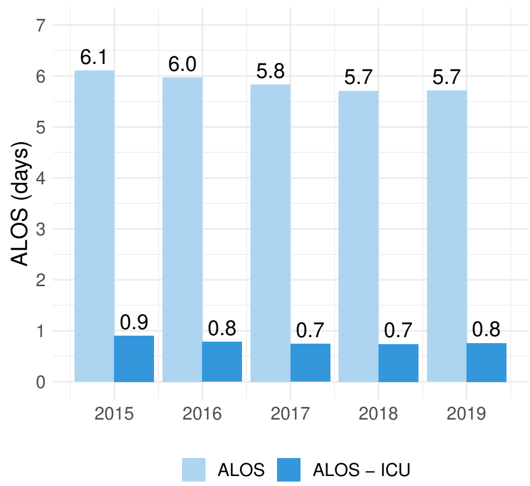


Source: CZSO (2022a)

Length of stay in our data

In our data, the average length of stay slightly differs from the data from CZSO (2022a) because not all medical procedures were considered for the analysis, and the sample of hospitals is limited as well. In the Figure 4.4, the left columns depict the development of ALOS in our sample, while the right ones show the development of ALOS in the intensive care unit. The trend of decreasing length of stay can be observed - the ALOS dropped by approximately half a day from 6.1 days in 2015 to 5.7 days in 2019. However, the average LOS - ICU changed only slightly; it decreased from 0.9 to 0.8 days. This measure, however, also includes the episodes of care for which the treatment at the intensive care unit is not usual - the average of such episodes of care is close to zero (for example, laparoscopic cholecystectomy or vaginal delivery). Moreover, 73.4% of hospital cases in our sample were not hospitalized at ICU. If we remove the episodes of care for which hospitalization at ICU is not usual from our calculations, the average length of stay in the intensive care unit increases to 1.3 days in 2015 and 1.1 days in 2019.

Figure 4.4: Average length of stay in our data



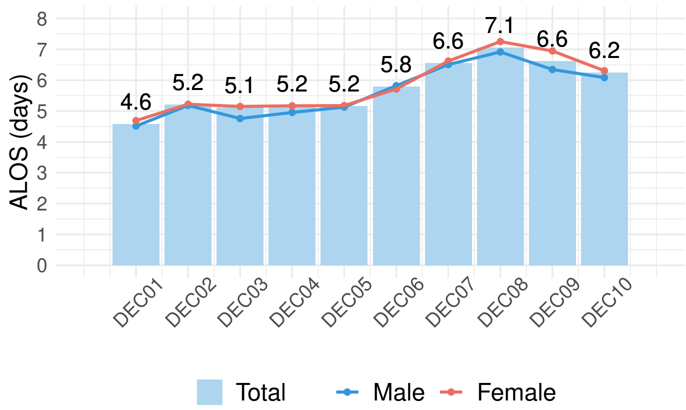
Source: Author's compilation

LOS by gender and age groups

In the analysis of LOS development over time, we also consider patient characteristics that might have an effect on patient's length of stay - one of such variables is the patient age. According to UZIS (2021), older people generally tend to have longer LOS. More precisely, the LOS increases especially after the age of fifty. This trend can be also observed in our data (Figure 4.5), where age is grouped by decennia. DEC 01 stands for patients aged 0-9 years, DEC 02 groups the patients aged from 10 to 19 years, etc. Children (DEC 01) usually have lower ALOS, then the ALOS increases but is quite stable until the age of fifty (DEC 05). After that it starts to grow gradually until the age of eighty (DEC08) when it drops. The decline for the last two depicted decennia might be caused by the limited sample in these groups and different proportion of treated cases in episodes of care - these older people could have undergone illnesses that have shorter LOS.

Figure 4.5 illustrates the described development, the bars capture the ALOS of all patients belonging to the given decennium, while lines show the ALOS by gender. This figure indicates that women have slightly longer LOS than men, which is in contradiction to UZIS (2021). According to UZIS (2021), LOS of men is longer at the age from 20 to 70, after that the situation changes and the ALOS of women is longer. The discrepancy between our data and UZIS might again be caused by the selection of episodes of care.

Figure 4.5: Average length of stay by gender & age groups

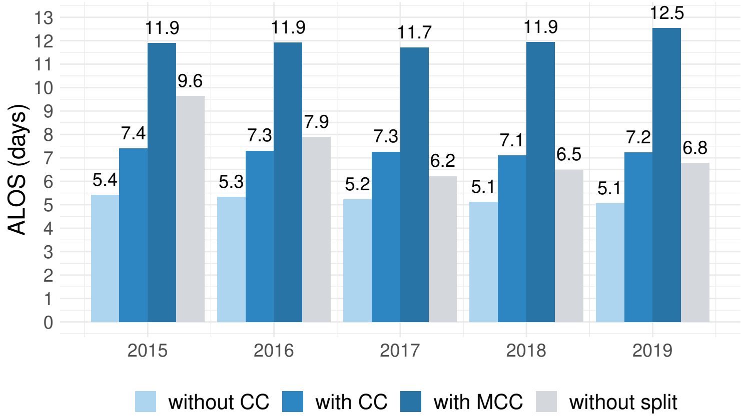


Source: Author's compilation

LOS by the level of complications & comorbidities (CC)

Another factor that might influence patient's length of stay is the level of complications and comorbidities. This variable serves in our analysis as a proxy for the severity of the case. It is derived from patient's IR-DRG group to which the patient was assigned. Thus, we can distinguish between 4 levels - the first three groups indicate the level of complications and comorbidities - without CC, patient with CC, patient with MCC. The last group, called without split, indicates that the hospital case was assigned to the DRG base that is not further split by the CC level. Therefore, in this situation, we are not able to determine the severity of hospital case. Figure 4.6 depicts the development of ALOS grouped by CC level. The graph suggests that people with a higher level of CC have on average longer LOS, which is in line with the intuition. It also offers us an interesting insight into the development of LOS over time. While the ALOS of patients with MCC did not change from 2015-2018 and even increased in 2019, the ALOS of patients in other groups decreased. The explanation for this trend might be that the hospitals managed to decrease LOS for less severe cases, whereas for more severe cases, they were not able to influence LOS that much.

Figure 4.6: Average length of stay by patients' CC level

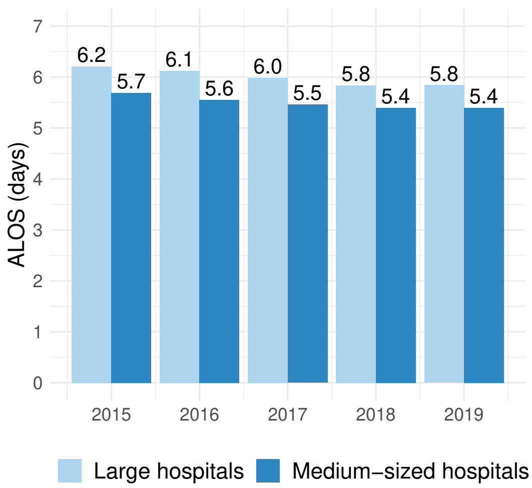


Source: Author's compilation

LOS by hospital type

The last graphical representation is dedicated to the comparison of LOS by hospital size, distinguishing between large and medium-sized hospitals. This categorization, however, is consistent with the division of hospitals by type to university and regional with the exception of two hospitals. Figure 4.7 illustrates the development of the average length of stay calculated in two size groups of hospitals.

Figure 4.7: Average length of stay by hospital size



Source: Author's compilation

The decline in ALOS can be observed in both groups; also the change between 2015-2019 is similar: 0.4 days for large and 0.3 days for medium-sized hospitals. The average length of stay is consistently longer in large hospitals compared to medium-sized hospitals. It might be caused by the structure of patients treated in each type of hospitals, as more complicated cases are usually admitted in large hospitals, whereas less complicated cases are hospitalized in medium-sized hospitals.

Chapter 5

Methodology

This chapter introduces the methodology that is used in this thesis to investigate the efficiency changes in inpatient care provision under the DRGs, measured by inpatient length of stay. In the first part of the analysis, we are interested whether the length of stay experienced significant statistical and clinical changes over time. In the second part, we investigate the hypothesis of standardization of care provision, measured by the development of LOS variation (specifically standard deviation of LOS). This chapter starts with formulating concrete hypotheses in Section 5.1. Next, the methodology is discussed, reflecting the structure of the analysis. First, the model for length of stay is explained in Section 5.2, then model for LOS variation is described in Section 5.3.

5.1 Hypotheses and their motivation

Although some foreign literature analyzing patient-level data and length of stay under DRG systems already exists, to the best of author's knowledge, there do not exist such studies concerning Czech patient-level data. Specifically, this study aims to scrutinize changes in efficiency of inpatient care in the Czech Republic between 2015 and 2019 under the DRG-based reimbursement mechanism. Focusing on inpatient length of stay, we formulate the following hypotheses:

Hypothesis #1: After the introduction of DRGs, hospitals were motivated to improve the efficiency of inpatient care, and thus, inpatient length of stay decreased significantly over time.

The decrease in length of stay can be observed from the aggregated data available from CZSO (2022a). However, we would like to analyze the trend after controlling for patient characteristics and other covariates. Our data cover the period that starts shortly after the implementation of DRG classification, which motivates more efficient healthcare provision that can also be measured by length of stay.

Even though the broader implementation of DRGs came into force already in 2012 and our data start three years later, we believe that the changes in hospitals' behavior were not sudden, but hospitals might have reacted with a lag and adapted the healthcare provision gradually. Moreover, our data capture the year when the preparation of refining Czech DRG started, project DRG-restart was launched, and it was confirmed that the Czech Republic would stick to the DRG-based reimbursement mechanism regarding inpatient care.

Under the hypothesis that the LOS development was not the same everywhere but might differ depending on hospital type, patient severity levels, or might have been experienced only for some episodes of care, we formulate three other hypotheses that extend the first hypothesis #1:

Hypothesis #1a: The size of the decrease in length of stay varies between hospital types.

Hospital size might affect the approach of the hospitals. The operation of large hospitals differs from medium-sized hospitals. The differences in hospital efficiency were already noted by Votápková *et al.* (2013) and Mastromarco *et al.* (2019). Thus, we would like to distinguish between the hospital types and analyze the time trend separately. We split our dataset by the size of hospitals in order to analyze whether the potential changes are driven only by one type of hospital, or if the size of the change differs.

Hypothesis #1b: The length of stay decreased more for less severe hospital cases - patients without complications and comorbidities, compared to LOS development of more severely ill patients - patients with complications and comorbidities.

Generally, systemic changes are easier to be implemented for less complicated cases. As for evaluating of hypothesis #1b, we subset our data set to patients without CC, with CC, and patients with MCC and compare the LOS development between these samples.

Hypothesis #1c: The development of length of stay differs across different episodes of care.

The LOS time trend is evaluated for five selected episodes of care separately - namely, for laparoscopic cholecystectomy, bowel resection, PTCA, hip replacement, and delivery. Heterogeneous episodes of care were chosen, meaning that they belong to different clinical areas and they also differ in other aspects, such as the intensity of treatment or the characteristics of treated patients.

Hypothesis #2: Hospitals tended to standardize the healthcare provision - the standard deviation of length of stay decreased over time.

With the standardized reimbursement per hospital case with a certain diagnosis under the DRG system ($\sim$ hospital revenue), hospital costs ($\sim$ length of stay) should be standardized as well. Thus, we expect to observe a decline in LOS standard deviation.

5.2 Length of stay (LOS) models

5.2.1 Theoretical background

As mentioned in the Section 3.1, length of stay is usually used to evaluate the efficiency of hospitals when information about the cost of hospitalization is not available. Length of stay, measured in days, is a count variable - the discrete nature of this regressand has to be taken into account when choosing the appropriate methodology. Regarding count data models, Poisson or negative binomial (NB) models are usually applied (e.g., Epstein *et al.*, 2010; Street *et al.*, 2012; Wolff *et al.*, 2015).

The selection criterion between these two models is the level of dispersion in the data, i.e., Poisson regression assumes equidispersion - the equality of conditional mean and variance: $\mu = E\left(y|\,\mathbf{x}\right) = Var\left(y|\mathbf{x}\right)$. However, in the case of length of stay, it often happens that this assumption is violated and the data are overdispersed - the distribution of LOS is right skewed and variance is higher than mean. In that case, the negative binomial model is preferred for overdispersed data. The most frequently used NB model (Cameron & Trivedi (1998) call it NB2) assumes variance as a quadratic function of mean:

$$Var\left(y|\,\mu,\alpha\right) = \mu + \alpha \cdot \mu^2, \alpha > 0. \tag{5.1}$$

And the probability density function has the following form:

$$f(y|\mathbf{x}) = \frac{\Gamma(y+\alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y},\ y=1,2,\ldots, \quad (5.2)$$

where $\Gamma(.)$ is a gamma function and α is a dispersion parameter. When α goes to 0, the NB model converges to Poisson model. The overdispersion can be verified by a test based on testing the dispersion parameter alpha with the null hypothesis $H_0 : \alpha = 0 \sim$ no overdispersion present, versus the alternative hypothesis $H_A : \alpha \neq 0 \sim$ overdispersion present (Cameron & Trivedi, 2005; 1998).

Truncation

The length of stay variable in our data has another important feature - truncation at zero, meaning that no hospital case has a zero length of stay. Thus, zero-truncated Poisson or zero-truncated negative binomial should be applied. For zero-truncated (ZT) models, the density function has the following form:

$$f(y|\theta, y \geq 1) = \frac{f(y|\theta)}{1-F(0|\theta)},\ y=1,2,\ldots, \quad (5.3)$$

where θ is a parameter vector and $F(.)$ is the cumulative distribution function of the respective distribution - Poisson or negative binomial (Cameron & Trivedi, 2005). Summing up, based on the assessment of LOS distribution and the test for overdispersion, we will use either zero-truncated negative binomial (ZTNB) or zero-truncated Poisson models for investigating the time trend of length of stay and for evaluating the first set of hypotheses #1 & #1a - #1c.

Coefficient interpretation

Since both negative binomial and Poisson are non-linear models, the size of regression coefficients cannot be directly interpreted. Hence, our results will be presented in the form of incidence rate ratios (IRR) and marginal effects at means (ME). Incidence rate ratios are calculated by exponentiation of coefficients and allow for multiplicative interpretation. Regarding marginal effects, when the variable is a dummy variable, the effect is calculated as the discrete change as the dummy variable changes from 0 to 1.

5.2.2 Model specification

Our model is highly inspired by the model proposed by Street *et al.* (2012) for examining how well diagnosis-related groups explain variations in LOS using patient-level data and hospital characteristics, the model mentioned in Section 3.2. In our analysis, we use the first stage of the model with several adaptations. We extend the model with the variable *year* to analyze the main research question - the development of LOS over time. We employ the variable as a dummy for each year, leaving year 2015 as a reference group), which should capture the time effects in the model. Then, instead of DRG groups, we use episodes of care, but we also include patient characteristics and dummy variables for hospitals.

Baseline model

The baseline model equation has the following form:

$$
\begin{aligned}
LOS_i = f\Big(\alpha + \sum_{j=1}^{4} \beta_j \cdot year_{j,i} + \sum_{k=1}^{6} \gamma_k \cdot age\_group_{k,i} + \delta_1 \cdot gender_i + \\
+ \delta_2 \cdot ICU_i + \sum_{l=1}^{3} \epsilon_{l,i} \cdot CC_{l,i} + \sum_{m=1}^{14} \mu_m \cdot hospital_{m,i} + \\
+ \sum_{n=1}^{33} \lambda_n \cdot episode\_of\_care_{n,i} + u_i\Big),
\end{aligned}
\tag{5.4}
$$

where LOS is the length of stay of patient i, α is a constant, u_i is an error term, $\beta, \gamma, \delta, \epsilon, \mu, \lambda$ are estimated coefficients for respective independent variables. Regressors are selected categorical variables from Table 4.3. Type of discharge was not included in the model, because the majority of hospital cases (97.8%) were discharged home. Moreover, the variable LOS-ICU was transformed to a dummy variable. Further explanation and expected effects of independent variables are summarized below.

Model independent variables and expected effects

- ***Year***: a dummy variable was created for each year; thus, we have five levels *year 2015 - year 2019*, *year 2015* was selected as a reference group in the model. We expect to observe decreasing time trend, thus variables *year 2016*, *year 2017*, *year 2018*, and *year 2019* should have negative (statistically significant) effect compared to the reference *year 2015*. The size of the effect should increase with the year, meaning that the effect of *year 2019* should be larger than the effect of *year 2018*. The effect of *year 2018* should be larger than the effect of *year 2017*, and so on. This is the main variable of interest with which we aim to evaluate the first hypothesis #1.

- ***Age group***: since we assume that age will have a significant effect, especially in higher decennia, we decided to slightly regroup the data. We grouped the second, third, and fourth decennium (people aged 10-39 years) since we do not assume much variability in LOS with respect to these age groups. This group, *DEC 02-04*, was defined as the base group. Moreover, we group the last two decennia *DEC 09*, and *DEC 10* (people aged 80+) because the latter group contained only a few observations. With higher age, LOS is assumed to be longer. Thus, dummy variables *DEC 06*, *DEC 07* and *DEC 08-10* should have a positive effect. Moreover, we expect that the size of this effect will increase with higher age groups.

- ***Gender***: by including this variable, we control for potential effect of gender on LOS. Male gender was chosen as the reference group. As can be seen in Figure 4.5, women have slightly longer LOS in our sample, hence we expect a positive coefficient for this variable.

- ***ICU***: *ICU* is a dummy variable equal to one if a patient spent at least one day of his/her hospitalization in the intensive care unit. It can be expected that these patients might have longer LOS. This variable is partially connected to the severity of case; however, there is only a weak correlation between CC level and dummy *ICU*, which indicates that the variable *ICU* might also be related to the treatment methods - sometimes a patient is placed to ICU after a procedure, disregarding the severity of illness. Moreover, some treatment processes do not allow to discharge a patient from the hospital to home directly from ICU, and he/she must stay some more time in the general ward. These all might prolong LOS.

- ***CC***: four dummy variables were created to distinguish between the four CC levels (*without CC*, *with CC*, *with MCC*, *without split*). More complicated cases are expected to have longer LOS compared to the cases without complications and comoridities (*without CC*), which were defined as a reference group.

- ***Hospital***: dummy variables for each except one hospital listed in Table 4.1 were included in the model in order to control for hospital characteristics that might influence the length of stay, for instance, hospital size, number of doctors, and hospital beds.

- ***Episode of care***: dummy variables for each but one episode of care listed in Table 4.2 were added to the model. They should capture the effects of episodes of care and the LOS variation caused by differences in severity and treatment methods between episodes of care. Vaginal delivery, as one of the episodes of care with the highest number of hospital cases, was left as a reference group.

Model extensions

We can obtain information on the general time effect from the baseline model (later also denoted as *Full sample* model). However, we miss the insight into the development of individual episodes of care, and we cannot evaluate potential differences in time effects between different hospital types or between patients with different illness severity levels. In order to get a better understanding of the potential heterogeneity of LOS development, we run models on three types of subsamples in order to get a better comprehension of the potential drivers of LOS development.

1. **Large and medium-sized hospitals** - the model will be regressed separately for samples of patients treated in large and medium-sized hospitals. Such division should evaluate the hypothesis that the development of LOS is driven by only one type of hospitals or that the size of the effect differs between large and medium-sized hospitals (hypothesis #1a). From now on, for simplicity, we will refer to the models concerning this type of subsamples as *Large* and *Medium-sized*.

2. **Subsamples by CC level** - As can be seen from Figure 4.6, there is evidence of a slightly larger decrease in LOS rather for hospital cases without complications and comorbidities. In order to explore this trend more and to evaluate hypothesis #1b, we will run a model only for the sample of patients without CC to evaluate how the size of the effect will

change, and we will compare it with the models concerning the sample of patients with CC and the sample of patients with MCC. From now on, for simplicity, we will refer to the models concerning this type of subsamples as *Without CC*, *With CC*, and *With MCC*.

3. **Episodes of care separately** - to be able to explore the LOS development in the individual episodes of care more (hypothesis #1c), the baseline model will be estimated for five selected episodes of care separately, namely - laparoscopic cholecystectomy, bowel resection, PTCA, total hip replacement (from now on called hip replacement), and delivery - which comprises both, vaginal delivery and cesarean section.

   The selected episodes of care were chosen primarily based on the number of cases with the aim of analyzing episodes of care with a high number of treated cases. Then, heterogeneous episodes of care were selected - that is, the selected episodes of care belong to different clinics (orthopedics, cardiology, surgery, ...), represent different types of treatment processes and complexity of procedure - for example, hip replacements are usually planned, whereas bowel resection is usually an acute procedure. Moreover, the selected episodes of care are also heterogeneous in terms of the usual patients' age. People undergoing hip replacement are usually older, while delivery is common in women in younger age.

The models differ from the baseline model, mainly in the sample selected; only minor adjustments to independent variables are made. The categorical variable *CC* is omitted in *Without CC*, *With CC*, and *With MCC* models. In episodes of care models, categorical variable *episode of care* is omitted except for the *Delivery* model, in which we distinguish between vaginal and cesarean delivery. Moreover, age groups are recategorized to be meaningful for each episode of care. For instance, patients hospitalized because of a hip replacement or PTCA are usually older patients, while patients undergoing delivery are mostly women of productive age. Moreover, one more adjustment was made to the *Delivery* model, that is, omitting variable *gender*, since this variable is not relevant in this case.

Clustered standard errors

In all models, clustered robust standard errors are estimated. Standard errors in models for individual episodes of care are clustered at the hospital level; in the remaining models, standard errors are clustered at the level of episodes of care.

5.3 Model for the development of variation in LOS

In the second part of the analysis, we will focus on variation in LOS measured by standard deviation. We will evaluate hypothesis #2 that not only the length of stay decreased in general, but also its standard deviation. In other words, we aim to investigate if inpatient care has been standardized under standardized reimbursement.

Model specification

As in the first part of the analysis, models will be run concerning various samples. First, LOS variation will be examined on the full sample. Then, the sample will be split into subsamples by two variables - subsamples based on hospital type (separate models for large and medium-sized hospitals) and subsamples based on severity level (separate models for the three CC levels). Lastly, the regressions will be run for the five selected episodes of care.

To evaluate the hypothesis of decreasing variation, we employ an ordinary least squares (OLS) regression. First, the standard deviation of length of stay ($sd(LOS)$) is computed separately for each episode of care in each hospital in each year. Standard deviations computed from small samples were omitted because of loss of robustness and potential bias caused by an outlier in a sample that would significantly affect the standard deviation. In other words, we discarded standard deviations computed from a sample of 30 or fewer observations. The computed standard deviation serves as the dependent variable. It is regressed on the following independent variables. Variables of interest are year dummy variables serving as time effects, and which will be compared with the reference group - year 2015. They are accompanied by two other sets of dummy variables, the first one represent the type of hospital, the second set captures the episode of care. To avoid multicollinearity, one hospital and one episode of care are not included in the model and form the baseline groups. Moreover, variable *without CC ratio* is added and expresses a proportion of cases without CC in a given year, episode of care, and hospital.

Using OLS regression requires evaluating its assumptions. To fulfill the assumption of normal distribution of a dependent variable, and because the standard deviation in our samples is right-skewed, we used a log-linear model, where the dependent variable is put into a logarithm. The potential problem of heteroscedasticity is addressed by robust standard errors that are clustered in the same way as models in the first part of the analysis. In *Full sample*, *Large*, *Medium-sized*, *With CC* and *Without CC* models, standard errors are clustered at the level of episodes of care, in models for episodes of care, standard errors are clustered at hospital level.

Summing up, we regress the LOS standard deviations on time effects, two types of categorical variables, and *without CC ratio*. The regression equation can be expressed as:

$$log(sd(LOS))_{jkl} = \alpha + \sum_{j=1}^{4} \beta_j \cdot year_j + \sum_{k=1}^{14} \gamma_k \cdot hospital_k + \\ + \sum_{l=1}^{33} \delta_l \cdot episode\_of\_care_l + \epsilon \cdot without\_CC\_ratio_{jkl} + u_{jkl} \tag{5.5}$$

where *log(sd(LOS))* is the logarithmic form of standard deviation of length of stay in year j, hospital k, and episode of care l. *Year*, *hospital*, *episode of care*, and *without CC ratio* represent the above-mentioned independent variables; α is a constant, $\beta, \gamma, \delta, \epsilon$ are the estimated coefficients, u_{jkl} is an error term. The regression equation is adjusted to each subsample – *without CC ratio* is discarded in *Without CC*, *With CC*, and *With MCC* models; *episodes of care* are omitted in episode of care models. Another variable - share of cesarean sections is included in *Delivery* model to capture the share of vaginal deliveries and cesarean sections that can potentially influence the standard deviation of length of stay.

As mentioned, the main variable of interest is again the categorical variable *year*. Leaving *year 2015* as the reference group, we expect to observe a similar decreasing effect as in the first part of the analysis - LOS models. Since we use log-lin models, the coefficients will be interpreted as percentages.

Chapter 6

Results

In this chapter, the author would like to present the results of the conducted analysis of changes in inpatient care provision when hospitals operate under DRG. The results concerning the development of length of stay are presented in two parts. Firstly, in Section 6.1, the author describes the results of the baseline – *Full sample* model and models on two types of subsamples (large vs. medium-sized hospitals and patients without CC vs. with CC vs. with MCC). Then, the author summarizes the models by episodes of care in Section 6.2. Results of models for LOS variance over time are divided similarly and presented in Section 6.3. The last part of this chapter is dedicated to evaluating hypotheses in Section 6.4 and discussing limitations in Section 6.5.

6.1 LOS models

Starting with the results that focus on the development of inpatient length of stay, in this section, the author presents the results of models that were specified in the Section 5.2, concerning full sample, and two types of subsamples based on hospital size and patient severity. Since the whole model results are too extensive to be presented and described in one table, in this chapter, the results are summarized in smaller parts, while the full results are included in the Appendix (Table A.4 and Table A.5). Firstly, estimated effects of the main variable of interest, time, are discussed, and consequently, other covariates, patient characteristics, are presented. Results are interpreted either in terms of marginal effects or as incidence rate ratios since both absolute and relative measures provide valuable information.

In all results tables presented in this section, the *Full sample* model results are stated in the first column, results of models concerning only large and medium-sized hospitals are listed in the second and third columns, and results for samples of patients without CC, with CC, and with MCC are shown in the fourth, fifth and sixth columns, respectively.

All models, except for the *Without CC* model, were estimated using zero-truncated negative binomial model since the dependent variable (LOS) exhibits overdispersion, as can be seen from Figure 6.1 and the table of summary statistics (Table 6.1) below. In these samples, its distribution is right-skewed with variance higher than the mean. The application of NB distribution was also verified by the overdispersion test, in which we could reject the null hypothesis of no overdispersion at 1% significance level in all five models. When estimating the *Without CC* model, we could not reject the null hypothesis of equidispersion, and thus, the model was estimated using the zero-truncated Poisson model. Standard errors were clustered at the level of episodes of care in all six models, and they are provided in all tables in parentheses.

Figure 6.1: Histograms of length of stay in examined samples

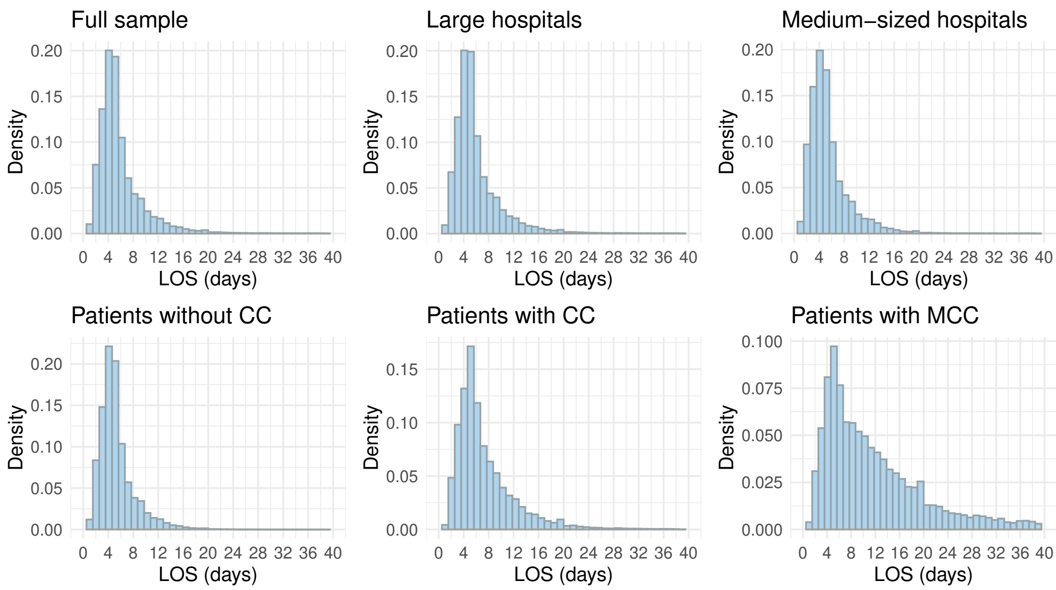


Table 6.1: Summary statistics of length of stay in examined samples

Sample	2015-2019					2015		2019	
	N	*Mean*	*SD*	*Var*	*Min/Max*	*Mean*	*SD*	*Mean*	*SD*
Full sample	536,782	5.86	4.09	16.73	1/72	6.10	4.44	5.71	3.95
Large hospitals	392,728	5.99	4.21	17.72	1/72	6.21	4.47	5.84	4.11
Medium-sized hospitals	144,054	5.48	3.71	13.76	1/54	5.69	4.31	5.40	3.53
Patients without CC	420,462	5.22	2.90	8.41	1/52	5.42	3.12	5.07	2.74
Patients with CC	92,337	7.26	4.98	24.80	1/71	7.41	5.15	7.24	4.98
Patients with MCC	21,764	11.99	9.21	84.82	1/72	11.90	9.88	12.54	8.92

Note: N=number of observations; SD=standard deviation; Var=variance

6.1.1 LOS over time

In five out of six models, we observe statistically significant negative effects of year dummy variables (Table 6.2 and Table 6.3). Regarding the *Full sample* model, the model estimates that hospitalizations in 2016 were on average shorter by 0.05 days in comparison to the year 2015. The effect is larger with each additional year which illustrates the downward trend in length of stay. Cases treated in the last observed year 2019 had shorter LOS by 0.32 days, ceteris paribus. The dummy variables of individual years indicate that the trend is not linear but size of changes differ year-to-year.

Even though we control for other possible causes of LOS changes in our models – mainly patient characteristics, but also hospital effects, the design of our study does not allow us to attribute the change over time fully to the implementation of DRG system. However, our finding describes the development that is intended when DRGs are introduced. Our findings correspond to the previous literature from Germany and Switzerland, which identifies the decrease in LOS under DRG (e.g., Böcking *et al.*, 2005; Koné *et al.*, 2019).

In broader context, an average hospital in our data set treated approximately 7,500 cases in 2019. The average decrease in length of stay (0.3 days) multiplied by the number of yearly treated cases equals 2,250 bed days that an average hospital saved in 2019 compared to a hypothetical scenario in which LOS would remain unchanged in the observed period. The saving of 2,250 bed days in an average hospital indicates the average saving of resources that a hospital can reallocate and possibly treat more patients.

Table 6.2: Year of discharge (Marginal effects)

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Year of discharge *(base = year 2015)*						
year 2016	-0.049* (0.030)	-0.041 (0.030)	-0.104** (0.043)	-0.025 (0.072)	-0.091 (0.065)	0.503*** (0.154)
year 2017	-0.155*** (0.039)	-0.141*** (0.037)	-0.226*** (0.055)	-0.218** (0.087)	-0.236*** (0.087)	0.035 (0.167)
year 2018	-0.267*** (0.045)	-0.254*** (0.057)	-0.343*** (0.052)	-0.420*** (0.091)	-0.402*** (0.090)	-0.215* (0.115)
year 2019	-0.323*** (0.045)	-0.327*** (0.054)	-0.368*** (0.067)	-0.383*** (0.088)	-0.391*** (0.081)	-0.131 (0.214)
Model	ZTNB	ZTNB	ZTNB	ZT Poisson	ZTNB	ZTNB
Observations	536,782	392,728	144,054	420,462	92,337	21,764

Note: *Length of stay* is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.4 in Appendix.

Table 6.3: Year of discharge (Incidence rate ratios)

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Year of discharge *(base = year 2015)*						
year 2016	0.991* (0.005)	0.993 (0.005)	0.980** (0.008)	0.986** (0.005)	0.987 (0.010)	1.050*** (0.016)
year 2017	0.971*** (0.007)	0.974*** (0.007)	0.956*** (0.010)	0.972*** (0.006)	0.965*** (0.013)	1.003 (0.017)
year 2018	0.951*** (0.008)	0.954*** (0.010)	0.933*** (0.010)	0.951*** (0.007)	0.940*** (0.013)	0.979* (0.011)
year 2019	0.940*** (0.008)	0.941*** (0.010)	0.928*** (0.013)	0.934*** (0.007)	0.942*** (0.012)	0.987 (0.021)
Model	ZTNB	ZTNB	ZTNB	ZT Poisson	ZTNB	ZTNB
Observations	536,782	392,728	144,054	420,462	92,337	21,764

Note: *Length of stay* is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.5 in Appendix.

6.1.2 Models by hospital size

The comparison of large and medium-sized hospitals indicates that a larger change in LOS over time was experienced in medium-sized (mainly regional) hospitals. Specifically, in medium-sized hospitals, LOS decreased by 0.37 days ($\sim$ 7.2 %) from 2015 to 2019, whereas in large hospitals, the decrease was only 0.33 days ($\sim$ 5.9%). This result might have various explanations – first, medium-sized hospitals usually treat less complicated cases (the average yearly share of patients without CC in medium-sized hospitals in our data is 81% compared to 77% in large hospitals), for which changes in inpatient care provision are easier to be implemented.

Second, large hospitals might be generally less resilient toward systemic changes because the organizational structure in those hospitals might be more complex. Thus, implementing changes in treatment methods leading to a decrease in length of stay or enhanced hospital efficiency might take longer. It might be supported by conclusions of Votápková *et al.* (2013), who note that larger and teaching hospitals tend to be less efficient. However, when Mastromarco *et al.* (2019) extended the previous study of hospital efficiency by taking into account also hospital DRG case-mix and the variable for publications and research, the effect of hospital size on hospital efficiency became insignificant. The researchers also explain that big and university hospitals usually treat more complicated cases, which supports our first argument.

Third, the initial condition of the two hospital groups should also be considered. It might reveal that initially, LOS in medium-sized hospitals was longer, and these hospitals thus had more space for improvement. However, as Table 6.1 suggests, LOS in 2015 in medium-sized hospitals was shorter than in large hospitals. This also supports the previously mentioned explanation regarding less severe cases in medium-sized hospitals.

Noteworthy, the difference between the effects is only 0.04 days (~ 1.3 pp), which is a nearly negligible effect and clinically not very meaningful.

6.1.3 Models by patient severity level

The second subsample comparison is dedicated to patients without CC, with CC, and with MCC. Starting with the model for patients with MCC, the decline in length of stay is not observed. LOS fluctuated over time – the coefficients of years indicate that it increased from 2015 to 2016, then it dropped and increased again in 2019. Furthermore, the coefficients are statistically significant only in two years - 2016 and 2018. The time trend for less severe cases – patients without and with CC is similar. We can observe a statistically insignificant decline in 2016, followed by a significant drop in the next two years 2017 and 2018 - in 2018, the LOS was shorter by 0.4 days compared to 2015. In 2019, LOS was slightly longer than in 2018, but the difference is not clinically meaningful. Even though the marginal effects indicate a larger effect for cases with CC compared to cases without CC, turning to relative values (IRR presented in Table 6.3), the effect is larger for cases without CC – LOS decreased over time by 6.6% for cases without complications while for cases with complications, LOS decreased by 5.8%.

Summing up, the decline in length of stay was not observed only in case of the most severely ill patients - patients with MCC. This supports our hypothesis that it is harder to influence LOS of more severely ill patients by systemic changes in inpatient care.

6.1.4 Patient characteristics

Age & Gender

Moving to patient characteristics that might affect length of stay, the Table 6.4 presents model results concerning the first two characteristics – age and gender.

Table 6.4: Age & Gender (Marginal effects)

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Age *(base = DEC 02-04)*						
DEC 01	-0.200	-0.143	-0.640***	-0.053	0.065	-0.810*
	(0.131)	(0.120)	(0.172)	(0.374)	(0.450)	(0.446)
DEC 05	-0.040	-0.051	0.007	-0.091	-0.077	0.107
	(0.054)	(0.060)	(0.055)	(0.065)	(0.047)	(0.150)
DEC 06	0.055	0.055	0.090	-0.112	-0.111	0.338*
	(0.092)	(0.096)	(0.108)	(0.093)	(0.074)	(0.202)
DEC 07	0.177	0.168	0.248*	-0.018	0.008	0.540**
	(0.111)	(0.110)	(0.136)	(0.099)	(0.076)	(0.216)
DEC 08	0.405***	0.393***	0.484***	0.240**	0.277***	0.844***
	(0.116)	(0.110)	(0.158)	(0.107)	(0.094)	(0.228)
DEC 09-10	0.764***	0.761***	0.818***	0.703***	0.792***	1.014***
	(0.169)	(0.166)	(0.198)	(0.154)	(0.182)	(0.178)
Gender *(base = male)*						
female	0.066	0.092	-0.007	0.026	0.098	-0.026
	(0.064)	(0.067)	(0.059)	(0.072)	(0.067)	(0.097)

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.4 in Appendix.

The patient age seems to have a significant effect on LOS only in the case of higher age groups compared to the reference age group (juveniles and people of working age). Focusing on *Full sample* model, people in their seventies (*DEC 08*) have longer LOS by 0.4 days; an even larger LOS difference (0.8 days) is estimated for the oldest age group - patients aged 80 and more. The result is in line with the intuition that older people are prone to suffer from more diseases and their treatment takes longer time; a similar effect was also estimated in previous literature (e.g., Tan *et al.*, 2013; Geissler *et al.*, 2012; Earnest *et al.*, 2006). In contrast, children have shorter LOS than the baseline group - however, this difference is not statistically significant.

The effect differs across the models both in terms of statistical significance and size. The largest differences are observed in *Without MCC* model – the gap between the oldest age group and the reference group exceeds one day. Likewise, the effect is significant and much larger for children (*DEC 01*) at a medium-sized hospital – children have shorter LOS by 0.6 days compared to the baseline group.

Regarding gender, it seems that females have slightly longer LOS than men in four out of six models, but the effect is neither statistically nor clinically significant (the effect size ranges between 0.07 to 0.1 days). In previous literature, the effect of gender differs depending on the episode of care studied - our results are similar to the findings of Gaughan *et al.* (2012), who also estimated non-significant effect of gender.

CC level & Stay in the intensive care unit

Results summarized in Table 6.5 indicate that CC level has both statistically and clinically significant effects on LOS. In comparison to the least severe cases, patients with CC have longer length of stay by 0.9 days concerning the *Full sample* model. More severe hospital cases, patients with MCC stay in the hospital even longer - the difference is 2.6 days compared to patients without CC. A very comparable result was estimated in models by hospital size. In models by severity level, this variable was omitted. Previous studies do not usually control for CC level - however, some studies employ Charlson Comorbidity Index instead, with the same aim - to control for patients' comorbidities. Studies by Geissler *et al.* (2012) or Häkkinen *et al.* (2012) reveal the same effect of the level of comorbidities on length of stay - according to the above-mentioned researchers, patients with more comorbidities tend to stay in hospital longer.

The second variable that might be related to the severity of hospital cases is the dummy variable ICU, which is equal to one if a patient spent part of his/her hospitalization at the intensive care unit. Model estimation indicates a significant and positive effect of this variable. Patients that spent some time in ICU have longer LOS by 1.6 days in the *Full sample* model. Intuitively, the effect is larger in the *With MCC model*, where the difference is 3.7 days. In terms of relative difference (Table 6.6), the increase in LOS caused by staying at ICU ranges from 32% to 47%, the largest is in *With MCC* model. In previous literature, the variable ICU admission was used by Tan *et al.* (2013), who also estimated longer LOS for patients admitted to ICU.

Table 6.5: CC level & ICU (Marginal effects)

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
CC level *(base = without CC)*						
with CC	0.888***	0.870***	0.938***	-	-	-
	(0.162)	(0.165)	(0.154)			
with MCC	2.557***	2.490***	2.785***	-	-	-
	(0.321)	(0.303)	(0.385)			
without split	1.802	1.604	2.540**	-	-	-
	(1.291)	(1.313)	(1.221)			
ICU *(base = no)*						
ICU (yes)	1.630***	1.672***	1.497***	2.458***	2.038***	3.714***
	(0.403)	(0.402)	(0.462)	(0.465)	(0.396)	(0.567)

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Variable CC level was not included in models by patient severity level. Complete results are shown in Table A.4 in Appendix.

Table 6.6: CC level & ICU (Incidence rate ratios)

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
CC level *(base = without CC)*						
with CC	1.178***	1.170***	1.201***	-	-	-
	(0.034)	(0.034)	(0.035)			
with MCC	1.512***	1.487***	1.596***	-	-	-
	(0.070)	(0.064)	(0.089)			
without split	1.361	1.314	1.544**	-	-	-
	(0.259)	(0.257)	(0.262)			
ICU *(base = no)*						
ICU (yes)	1.336***	1.338***	1.327***	1.321***	1.354***	1.472***
	(0.091)	(0.089)	(0.109)	(0.093)	(0.078)	(0.093)

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Variable CC level was not included in models by patient severity level. Complete results are shown in Table A.5 in Appendix.

6.2 LOS models by episodes of care

In this section, the results focus on five selected episodes of care, which were estimated separately to analyze whether the results described in the previous section differ between the individual episodes of care. The heterogeneous episodes of care were chosen to cover different types of procedures and hospitalizations. As before, results were split into multiple tables for clarity. Results in this section are presented mainly as marginal effects, but when meaningful, they are followed by results in the form of IRR. The whole results are included in Appendix (Table A.6 and Table A.7).

The results for the individual episodes of care are ordered in tables as follows: laparoscopic cholecystectomy, bowel resection, PTCA, hip replacement, and delivery. The problem of overdispersion arose only in two out of five models (bowel resection and PTCA). These models were estimated using zero-truncated negative binomial, while zero-truncated Poisson was used for the remaining three episodes of care. Standard errors were clustered at hospital level. Summary statistics of LOS variable split by episodes of care is presented in Table 6.7, providing more detailed information about LOS distribution in individual samples of episodes of care as well as the comparison of conditional means in years 2015 and 2019. Bowel resection with the ALOS of 15.38 days is the most resource-intensive within the five selected episodes of care. In comparison, PTCA has the shortest average length of stay from the five selected episodes of care.

Table 6.7: Summary statistics of length of stay in subsamples by episodes of care

Sample	2015-2019					2015		2019	
	N	*Mean*	*SD*	*Var*	*Min/Max*	*Mean*	*SD*	*Mean*	*SD*
Lapar. cholecys.	17,430	5.18	2.17	4.71	2/12	5.36	2.12	5.10	2.20
Bowel resection	15,537	15.38	8.48	71.91	1/54	16.28	9.75	14.68	7.50
PTCA	45,156	4.23	2.92	8.53	1/18	4.41	3.13	4.02	2.60
Hip replacement	12,154	11.07	3.18	10.11	2/25	11.60	3.20	10.72	2.99
Delivery	154,141	5.20	1.91	3.64	1/13	5.34	1.93	5.08	1.91

Note: N=number of observations; SD=standard deviation; Var=Variance; Lapar. cholecys. = Laparoscopic cholecystectomy

6.2.1 LOS over time

Estimation of LOS development over time in the individual episodes of care confirms the finding from the previous section, that is, length of stay decreased in the examined period in all five episodes of care. As can be seen in Table 6.8, compared to the reference year 2015, the effect of each additional year grows and results in the decrease in 2019 that ranges between 0.2 days for delivery and 1.2 days for bowel resection. In relative terms (presented in Table 6.9), the effect is the largest for PTCA, for which the estimated decrease in LOS between 2015 and 2019 is 9.4%; on the other hand, delivery experienced the smallest relative decrease, precisely 3.8%.

Table 6.8: Episodes of care: Year of discharge (Marginal effects)

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Year of discharge *(base = year 2015)*					
year 2016	-0.122	-0.162	-0.017	-0.273	-0.013
	(0.078)	(0.229)	(0.064)	(0.248)	(0.049)
year 2017	-0.190*	-0.401	-0.017	-0.507	-0.072
	(0.111)	(0.276)	(0.086)	(0.330)	(0.058)
year 2018	-0.237***	-0.827**	-0.310***	-0.732**	-0.121***
	(0.091)	(0.345)	(0.064)	(0.357)	(0.043)
year 2019	-0.298***	-1.237***	-0.359***	-0.988***	-0.197***
	(0.088)	(0.255)	(0.079)	(0.298)	(0.048)
Model	ZT Poisson	ZTNB	ZTNB	ZT Poisson	ZT Poisson
Observations	17,430	15,537	45,156	12,154	154,141

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.6 in Appendix.

Table 6.9: Episodes of care: Year of discharge (Incidence rate ratios)

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Year of discharge *(base = year 2015)*					
year 2016	0.977	0.989	0.996	0.976	0.997
	(0.015)	(0.015)	(0.017)	(0.021)	(0.009)
year 2017	0.964*	0.974	0.996	0.956	0.986
	(0.021)	(0.018)	(0.022)	(0.028)	(0.011)
year 2018	0.955***	0.946**	0.919***	0.937**	0.977***
	(0.017)	(0.022)	(0.016)	(0.030)	(0.008)
year 2019	0.943***	0.919***	0.906***	0.914***	0.962***
	(0.016)	(0.016)	(0.019)	(0.024)	(0.009)
Model	ZT Poisson	ZTNB	ZTNB	ZT Poisson	ZT Poisson
Observations	17,430	15,537	45,156	12,154	154,141

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.7 in Appendix.

Noteworthy, laparoscopic cholecystectomy is one of the episodes of care that are nowadays discussed as those that might be transformed into a so-called one-day surgery, meaning that the patients would not stay in the hospital overnight but would be admitted and discharged within one day instead (MZČR, 2023b). Thus, the observed decline in LOS over time is a favorable trend toward one-day surgery. However, the conditional mean LOS for laparoscopic cholecystectomy in 2019 in our data is approximately 5 days, which is quite far from the planned one-day treatment. To sum it up, although LOS is decreasing, a much larger decrease is needed to reach the target of 1 day.

6.2.2 Other covariates

Effects of other covariates in models for individual episodes of care will not be discussed individually as in the case of the previous group of models, they will be all summarized within one subsection instead. Results are presented in Table 6.11 and Table 6.12. Since the age groups were not consistent across different episodes of care, their results require a more complex table compared to other variables. Hence, they are presented in a separate table, Table 6.10.

Turning to age, the positive effect of age on length of stay was estimated in four out of five models. Age was not a statistically significant determinant only in the model dealing with delivery.

Table 6.10: Episodes of care: Age (Marginal effects)

Age group	(1) Lapar. cholecys.	(2) Bowel resection	**Age group**	(3) PTCA	(4) Hip replace.	**Age group**	(5) Delivery
DEC01	0.276* (0.160)	1.259 (1.117)	DEC 01-05	base	base	DEC 02	base
DEC 02-04	base	base	DEC 06	0.017 (0.035)	-0.027 (0.162)	DEC 03	-0.011 (0.038)
DEC 05	-0.023 (0.039)	-0.131 (0.462)	DEC 07	0.182*** (0.028)	0.243** (0.109)	DEC 04	-0.051 (0.037)
DEC 06	0.034 (0.041)	-0.027 (0.416)	DEC 08	0.436*** (0.039)	0.678*** (0.144)	DEC 05	-0.012 (0.041)
DEC 07	0.239*** (0.046)	0.408 (0.404)	DEC 09-10	1.006*** (0.084)	1.258*** (0.171)		
DEC 08	0.561*** (0.064)	0.923* (0.495)					
DEC 09-10	1.019*** (0.109)	2.305*** (0.493)					

Note: Lapar. cholecys. = Laparoscopic cholecystectomy, Hip replace. = Hip replacement. *Length of stay* is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.6 in Appendix.

In the case of gender, the models provide mixed findings. Gender is statistically significant for laparoscopic cholecystectomy and PTCA; however, while LOS of females is shorter in the laparoscopic cholecystectomy model by 0.2

days, LOS of females in the PTCA model is longer by 0.1 days. Nevertheless, clinically, these differences are negligible.

Regarding the severity of a hospital case (CC level), the effect is in line with the *Full sample* model, the size of the effect differs, possibly reflecting the intensity and complexity of the treatment that is required by the individual episodes of care. While patients with MCC being hospitalized because of laparoscopic cholecystectomy have longer LOS compared to patients without CC by 1.6 days ($\sim$ 33%); in the case of bowel resection, the difference is 9.8 days ($\sim$ 83 %).

The variability can also be observed in the ICU variable, which distinguishes between cases that stayed at ICU and those that did not. While spending part of the hospital stay at the ICU prolongs length of stay by 0.6 days ($\sim$ 5.5%) for hip replacement, in the case of PTCA, LOS is prolonged by 2.8 days ($\sim$ 96%). A positive but not statistically significant effect was estimated for delivery, which is in line with the intuition that it is not usual being hospitalized in ICU during childbirth.

The delivery model was supplemented by a dummy variable indicating whether the childbirth was a vaginal delivery or a cesarean section. The model estimated that LOS for cesarean sections is longer by 1.3 days.

Table 6.11: Episodes of care: Other covariates (Marginal effects)

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Gender *(base = male)*					
female	-0.160*** (0.037)	0.008 (0.156)	0.082** (0.034)	0.099 (0.064)	-
CC level *(base = without CC)*					
with CC	0.642** (0.279)	3.865*** (0.399)	1.162*** (0.168)	0.809*** (0.167)	0.472*** (0.062)
with MCC	1.636*** (0.170)	9.785*** (0.426)	1.957*** (0.111)	2.174*** (0.359)	0.752*** (0.131)
without split	-	26.260*** (1.424)	3.254*** (0.419)	-	0.182 (0.141)
ICU *(base = no)*					
ICU (yes)	1.553*** (0.189)	2.818*** (0.372)	2.841*** (0.268)	0.578*** (0.102)	0.284 (0.196)
Additional variable					
Cesarean section	-	-	-	-	1.326*** (0.186)

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.6 in Appendix.

Table 6.12: Episodes of care: Other covariates (Incidence rate ratios)

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Gender *(base = male)*					
female	0.969*** (0.007)	1.001 (0.011)	1.022** (0.009)	1.009 (0.006)	-
CC level *(base = without CC)*					
with CC	1.129** (0.057)	1.328*** (0.038)	1.347*** (0.054)	1.075*** (0.016)	1.094*** (0.013)
with MCC	1.330*** (0.036)	1.831*** (0.046)	1.585*** (0.039)	1.201*** (0.033)	1.150*** (0.026)
without split	-	3.230*** (0.123)	1.972*** (0.130)	-	1.036 (0.028)
ICU *(base = no)*					
ICU (yes)	1.316*** (0.040)	1.230*** (0.037)	1.964*** (0.118)	1.055*** (0.010)	1.056 (0.039)
Additional variable					
Cesarean section	-	-	-	-	1.276*** (0.025)

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01. Complete results are shown in Table A.7 in Appendix.

6.3 Development of variation in LOS

In the last part of our analysis, we focus on the development of LOS variation and investigate the time trend of standard deviation of LOS within hospital within episode of care. Table 6.13 presents abridged regression results for the first set of models with a focus on the time effects. The estimated results suggest a downward but not linear trend over the five-year period. All dummy variables coefficients are negative and significant at 5% significance level. Focusing on the *Full sample* model, standard deviation of length of stay in 2016 was lower by 6.2% compared to year 2015, ceteris paribus. In 2017, standard deviation further decreased and was 9.3% lower than in 2015. The effect of the following two years is very similar – we observe a decrease by 14.6% in 2018 and by 14.4% in 2019.

In other words, we observe a considerable drop in the standard deviation of LOS in 2016 and 2017. Then, the standard deviation decreased in the following year 2018 by further 5.3 percentage points but increased negligibly from 2018 to 2019. Such results indicate that hospitals might have standardized treatments in hospitals.

The results are consistent in terms of the trend across the six models summarized in Table 6.13. Subsamples results indicate a similar decline as in the *Full sample* model. The smallest relative change in standard deviation is for large hospitals, for which we observe the decrease of 13%. The largest relative change in the standard deviation is observed for hospital cases with MCC – the decrease of 19% between years 2015 and 2019. Surprisingly, the decline is also observed in the *With MCC* model, which indicates that length of stay was standardized also for more severely ill patients, even though the length of stay itself did not decline as was commented in Subsection 6.1.3.

The additional variable *without CC ratio* yields the expected negative effect - a higher share of patients without CC leads to a decrease in the standard deviation. This finding might be interpreted in the following way: the higher share of patients without CC a hospital treats, the more homogeneous hospital cases it has; this homogeneity then leads to a more standardized length of stay.

Table 6.13: Variation in length of stay over time

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Year of discharge						
(base = year 2015)						
year 2016	−0.062***	−0.055***	−0.080**	−0.079***	−0.046**	−0.070**
	(0.018)	(0.020)	(0.035)	(0.022)	(0.022)	(0.031)
year 2017	−0.093***	−0.080***	−0.124***	−0.079***	−0.106***	−0.102***
	(0.017)	(0.019)	(0.034)	(0.021)	(0.023)	(0.033)
year 2018	−0.146***	−0.132***	−0.174***	−0.141***	−0.143***	−0.167***
	(0.021)	(0.019)	(0.043)	(0.024)	(0.022)	(0.032)
year 2019	−0.144***	−0.130***	−0.170***	−0.156***	−0.134***	−0.192***
	(0.019)	(0.019)	(0.039)	(0.022)	(0.022)	(0.034)
without CC ratio	−0.230***	−0.209***	−0.342***	-	-	
	(0.061)	(0.061)	(0.136)			
Constant	1.959***	1.934***	0.906***	1.460***	1.779***	2.016***
	(0.047)	(0.049)	(0.090)	(0.047)	(0.040)	(0.044)
Hospital effects	included	included	included	included	included	included
Episode of care effects	included	included	included	included	included	included
Observations	1,813	1,145	668	1,686	744	218
R^2	0.886	0.925	0.842	0.802	0.903	0.966

Note: Logarithm of standard deviation of length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01.

6.3.1 Individual episodes of care

After restricting the sample to individual episodes of care, its size drops significantly, which requires a careful interpretation of the results, since there might be a lack of statistical power to estimate statistically significant results.

As summarized in Table 6.14, the downward trend observed in the previous set of models is estimated only for bowel resection and PTCA, where the decrease in LOS standard deviation is much larger compared to the *Full sample* model - 26% and 21%, respectively. In the remaining three episodes of care, the time effect is not observed. Fluctuating but not statistically significant time trend was estimated for laparoscopic cholecystectomy and delivery. The time effects also fluctuate in the model for hip replacement, but they are statistically significant.

Table 6.14: Length of stay variation by episodes of care

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Year of discharge *(base = year 2015)*					
year 2016	−0.010	−0.131***	−0.028	−0.106**	0.017
	(0.034)	(0.023)	(0.029)	(0.044)	(0.016)
year 2017	−0.023	−0.150***	−0.038	−0.098**	−0.013
	(0.034)	(0.019)	(0.030)	(0.047)	(0.018)
year 2018	−0.014	−0.196***	−0.206***	0.042	0.005
	(0.035)	(0.024)	(0.030)	(0.040)	(0.018)
year 2019	−0.008	−0.264***	−0.205***	−0.047	0.007
	(0.036)	(0.019)	(0.031)	(0.035)	(0.018)
without CC ratio	−0.508**	−0.243	−0.022	−0.126	0.092
	(0.229)	(0.149)	(0.091)	(0.149)	(0.079)
Cesarean section	-	-	-	-	0.857***
					(0.168)
Constant	1.075***	2.430***	1.136***	1.231***	−0.076
	(0.221)	(0.074)	(0.075)	(0.126)	(0.063)
Hospital effects	included	included	included	included	included
Observations	70	70	59	65	65
R^2	0.816	0.810	0.931	0.701	0.925

Note: Logarithm of standard deviation of length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01.

The significance of the time effect reflects the distribution of length of stay described in the first part of the analysis. Those episodes of care that were right-skewed and featured overdispersion experienced a decline in LOS standard deviations over time, while we do not observe this trend for the episodes of care that were estimated using Poisson distribution. One possible explanation of the inconsistent time effect across the episodes of care might be that the healthcare provision was already standardized enough in some episodes of care, and thus, we did not observe significant changes in the LOS variation during the examined period. Inconsistent trends and differences between procedures and diagnoses were also discovered by van de Vijsel *et al.* (2015). Moreover, the aforementioned researchers found stable LOS variance for cholecystectomy and hip replacement as well. In comparison to the first set of models, the variable indicating the share of cases without CC is significant only for cholecystectomy, while we observe a negative but insignificant effect in the remaining models except for the model for delivery.

6.4 Evaluation of hypotheses

Section 5.1 introduces hypotheses based on the literature, DRG design, and clinical and economic background. In this section, we will summarize the results for each hypothesis.

Hypothesis #1: After the introduction of DRGs, hospitals were motivated to improve the efficiency of inpatient care, and thus, inpatient length of stay decreased significantly over time.

The trend of declining length of stay was observed, precisely LOS decreased by 0.3 days between 2015 and 2019. The trend was not linear but the size of change varied year-to-year.

Further, the resource savings that the LOS decrease brought may be expressed in bed days when multiplying the decrease by the number of treated cases.Concerning episodes of care selected for our analysis, it was calculated that the decrease of 0.3 days means saving 12,250 bed days per year for an average hospital in our sample. A hospital can use these saved bed capacities to treat more patients, and in the case of elective surgeries, patients might wait shorter time for the hospitalization.

The estimated development of length of stay is in line with the intention of DRG implementation, and it indicates the improvement in hospital efficiency over time. Moreover, the finding coincides with the prior literature, which also observes a decline in length of stay after the DRG introduction (Koné *et al.*, 2019).

Hypothesis #1a: The size of the decrease in length of stay varies between hospital types.

The time trend of LOS was evaluated separately for large and medium-sized hospitals. Results confirmed the trend of declining LOS and revealed a slightly larger decline at medium-sized hospitals; however, the difference between the two types of hospitals was clinically negligible.

Hypothesis #1b: The length of stay declined more for less severe hospital cases.

Models reveal a larger relative decrease in length of stay for cases classified as without complications and comorbidities. On the other hand, the hypothesis of declining LOS was not confirmed for cases with major complications and comorbidities, more severely ill patients.

Hypothesis #1c: The development of length of stay differs across different episodes of care.

The robustness of LOS development was confirmed when considering five selected episodes of care. LOS dropped in all five episodes of care studied, but the size of change varies. While the size of decrease in LOS exceeded one day ($\sim$ 8%) for bowel resection, it was only 0.2 days ($\sim$ 4%) for delivery. The variance in development suggests the individual approach of hospitals to each episode of care.

Hypothesis #2: Hospitals tended to standardize the healthcare provision - the standard deviation of length of stay decreased over time.

Analysis revealed the decreasing variation in length of stay within hospitals within episodes of care during the observed period. Specifically, the variation, measured by the standard deviation of LOS, decreased by 14.4% from 2015 to 2019. The estimates suggest that the drop was not linear and stabilized in the last two years of the observed period. In addition, the results are robust when distinguishing between two sizes of hospitals and patient severity levels. However, the same trend was not proven when analyzing some episodes of care separately. In this case, several possible explanations exist, but most importantly, we have to take into account the lower statistical power of these models for individual episodes of care. This result indicates the presence of standardization of inpatient care that contributes to reducing unnecessary variation in health care delivery and help to improve health care quality.

6.5 Limitations

There are some limitations to this study. First, to be able to fully recognize the pure impact of the introduction of DRG-based reimbursement mechanism on hospitals' care provision and length of stay, other methodology, for example, difference-in-differences design, might be more appropriate (as was used by Boes & Napierala (2021) or Cheng *et al.* (2012)). Unfortunately, the data that we have available for the analysis do not allow for such an approach. However, after controlling for patient characteristics, hospital, and episode of care effects, the author believes that the observed time-trend sheds some light on the dynamics of inpatient length of stay when hospitals continuously adapt to the gradual implementation of DRG in the Czech Republic.

Second, certain study limitations are associated with using patient-level data. One of them is a potential measurement bias related to the way the data are recorded by the hospitals. Another issue is potential bias caused by omitting relevant explanatory variables that were unavailable in our dataset. Specifically, the CC level was used as a proxy for patient severity and might be prone to issues related to the coding of hospital cases by hospitals within the IR-DRG classification. Thus, other patient clinical data might describe the variation of LOS even better, for example, number of diagnoses, specification of comorbidities, or more information about the treatment. Examples of other variables that may also provide valuable information are the level of emergency or information about admission. Unfortunately, our dataset does not contain this information.

Chapter 7

Conclusion

Expenses on inpatient care account for the largest share of health expenditure in the Czech Republic, which raises discussions on its efficiency. In addition, inpatient care has experienced quite large development in reimbursement in the last decade - the diagnosis-related group (DRG) system was introduced. Hospitals are reimbursed a fixed amount per hospital case within the DRG-based reimbursement mechanism. The DRG design aims to improve efficiency and transparency of inpatient care.

This thesis analyzes the development of inpatient care provision in the Czech Republic shortly after the broader implementation of DRGs in 2012. Understanding its dynamics is important for further potential adjustments to the reimbursement mechanism. Using panel-level data from 15 Czech hospitals from the period between 2015 and 2019 allows us to estimate the time trend of inpatient length of stay (LOS), which is broadly used in the literature as an indicator of hospital efficiency.

The first part of the analysis focuses on the development of length of stay and employs count data models, namely zero-truncated Poisson and zero-truncated negative binomial models. Moreover, we also control for other factors that may affect the length of stay - specifically, we take into account patient-level characteristics such as age, gender, and severity level. Also, the effects of hospitals and episodes of care were added to the model in order to cover potential LOS variation between hospitals and episodes of care.

Results of the models reveal that the length of stay decreased during the observed period by approximately 0.3 days. The downward trend was robust when considering hospital size, five individual episodes of care, or patient severity level. The exception, where the gradual decline was not estimated, is the subsample of patients with major complications and comorbidities. Regarding the development in individual episodes of care, which were chosen to be heterogeneous and cover different types of hospitalizations, the size of the decrease varies across episodes of care, indicating an individual approach of hospitals in each episode of care.

Observing the decline in length of stay is in line with the intended effects when DRGs are implemented, and it corresponds to the findings of prior literature (Koné *et al.*, 2019; Louis *et al.*, 1999). Moreover, decreasing LOS suggests improvement in the efficiency of inpatient care, which allows hospitals to treat more patients using the same capacity or to reallocate the capacity.

The second part of the analysis is dedicated to the development of the LOS variation, measured by the standard deviation of length of stay within hospitals within episodes of care. In this case, OLS regressions were estimated. A downward trend was also identified; the variation of LOS decreased nonlinearly by 14%. This finding is robust considering hospital size and patient severity level but differs between individual episodes of care. Such a result may be interpreted in the way that inpatient care in terms of LOS seems to be standardizing.

Despite the limitations caused by the data availability, such as potential omitted variable bias or the need for an even longer period examined, we believe that this thesis contributes to the current knowledge about the efficiency of hospitals under the DRG-based reimbursement mechanism in the Czech Republic. First, to the best of the author's knowledge, there does not exist much literature on the development of length of stay in the Czech environment. Moreover, the study is based on a unique dataset consisting of a quite large sample of patient-level data which is undoubtedly one of the contributions as well.

Nevertheless, only one perspective on inpatient care provision was analyzed, while some other questions regarding efficiency of inpatient care under DRG-based reimbursement mechanism still remain to be explored. First, the analyzed data come from the period of the IR-DRG system, but soon, the data from the refined DRG design, CZ-DRG, will be available, and further analysis of hospital efficiency thus might be possible and may bring updated findings.

Second, the measure of costs rather than length of stay might illustrate the situation of resource utilization more complexly. Third, other potential effects of DRG on hospitals' care provision already noted in foreign studies may also be considered - for example, readmission rate or mortality which are closely associated with quality of care. Such analysis, however, requires more extended data that track the whole patient history; for instance, payer data would be needed.

To conclude, the author believes that this thesis fills in the gap in the rather limited current Czech literature on the topic of inpatient care efficiency. More precisely, the thesis sheds more light on the changes in the efficiency of inpatient care provision after implementing the DRG-based reimbursement mechanism and confirms the decrease in length of stay over the examined period, which serves as an indicator of improved efficiency of inpatient care. However, given some limitations of the dataset available to the author, there still remains room for further research.

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Appendix A

Additional tables

Table A.1: List of medical procedures which define episodes of care

Episode of care (Czech)	Episode of care (English)	Procedures
Aortokoronární bypassy	*Aortocoronary bypass surgery*	07000, 07001, 07002, 07003, 07004, 07005, 07006, 07007, 07008, 07009, 07010, 55414, 55801
Císařský řez	*Cesarean section*	63125, 63127, 63129, 63131
Endarterektomie	*Endarterectomy*	54310, 54320, 07417, 07288, 07287, 07284, 56121, 07285, 07286, 07289
Gastrektomie	*Gastrectomy*	51387, 90875, 51385, 90884, 90879
Cholecystektomie laparoskopická	*Laparoscopic Cholecystectomy*	90818
Cholecystektomie otevřená	*Open cholecystectomy*	51371
Implantace kardiostimulátoru	*Pacemaker implantation*	55213, 55211, 55219, 17625, 07234

Continued on next page

Continuation of Table A.1

Episode of care (Czech)	Episode of care (English)	Procedures
Implantace kardioverteru - defibrilátoru	*Cardioverter - defibrillator implantation*	55213, 55211, 55219, 17625, 07234
Katetrizační ablace - komplexní	*Catheter ablation – complex*	17312
Kýla - děti 3-15 let	*Hernia - children 3-15 years*	52313
Kýla - děti do 3 let	*Hernia - children under 3 years*	52311
Kýla - dospělí	*Hernia - adults*	51517, 51511, 51515, 51513, 61461, 90796, 51519, 90838, 51518, 90824
Náhrada chlopně	*Valve replacement*	07041, 07042, 07043, 07044, 07051, 07052, 07053, 07057, 07058, 07059, 07121, 07122, 91972, 91973
Nefrektomie	*Nephrectomy*	090866, 90937, 76483, 76479, 76477, 76481, 76707, 76654
Odstranění paratyreoidálního tumoru	*Parathyroid tumour removal*	51131, 51133
Operace povrchových končetinových žil	*Superficial limb vein surgery*	54930, 07494, 07488, 07498, 07493, 07492, 07495, 07489, 07496, 07497
PTA	*PTA*	89423
PTCA	*PTCA*	89435, 89437

Continued on next page

Continuation of Table A.1

Episode of care (Czech)	Episode of care (English)	Procedures
Rekonstrukční artroskopie	*Reconstructive arthroscopy*	66041
Resekce plic anatomická	*Anatomical lung resection*	57247, 57245, 90870, 57249, 90869, 90871
Resekce plic extraanatomická	*Extra-anatomical lung resection*	90842, 57251
Resekce prsu	*Breast resection*	51233, 51237, 51235, 61449, 61455, 61447, 61453
Resekce střeva	*Bowel resection*	51359, 90864, 51388, 51355, 51361, 90858
Složitá artroskopie	*Complex arthroscopy*	66039
TEP kolene	*Total knee replacement*	66651
TEP kyčle	*Total hip replacement*	66612
TEP na horní končetině	*Total joint replacement in the upper extremity*	66449
Tonzilektomie	*Tonsillectomy*	71763, 71798
Transuretr. resekce tumoru moč. měchýře	*Transurethral resection of bladder tumour*	76559, 76557
Transuretrální prostatektomie	*Transurethral prostatectomy*	76533, 76603
Tyreoidektomie	*Thyroidectomy*	51125, 51127, 51121, 51129
Uzavření defektu kožním lalokem	*Closure of the defect with a skin flap*	61147, 61149, 61151, 61153, 61155
Vaginální porod	*Vaginal delivery*	63119, 63120, 63121, 63123

Continued on next page

Continuation of Table A.1

Episode of care (Czech)	Episode of care (English)	Procedures
Výkony na aortální chlopni	*Aortic valve procedures*	07011, 07012, 07013, 07014, 07015, 07016, 07018, 07019, 07020, 07021, 07022, 07023, 07029, 07030, 07031, 07032, 07036

Note: TEP = totální endoprotéza. The procedures are summarized using codes, the names of procedures can be found in the List of Health Services published by MZČR (2023a)

Table A.2: Summary statistics of categorical variables

Variable	Observations	Percent	Variable	Observations	Percent
Year of discharge			**Gender**		
year 2015	90,355	16.83	male	230,758	42.99
year 2016	109,436	20.39	female	306,024	57.01
year 2017	111,765	20.82			
year 2018	112,336	20.93	**CC**		
year 2019	112,890	21.03	without CC	420,462	78.33
			with CC	92,337	17.20
Age group			with MCC	21,764	4.05
DEC01	13,764	2.56	without split	2,219	0.41
DEC02	12,394	2.31			
DEC03	73,414	13.68	**ICU dummy**		
DEC04	112,829	21.02	no	394,125	73.42
DEC05	49,873	9.29	yes	142,657	26.58
DEC06	58,025	10.81			
DEC07	98,266	18.31	**Type of discharge**		
DEC08	86,852	16.18	home	524,704	97.75
DEC09	28,701	5.35	social care facil.	12,078	2.25
DEC10	2,664	0.49			

Note: social care facil. = social care facilities, hospital frequencies not provided because of data protection

Table A.3: Summary statistics of episodes of care

Variable	Observations	Percent
Anatomical lung resection	2,964	0.55
Aortic valve procedures	3,486	0.65
Aortocoronary bypass surgery	8,688	1.62
Bowel resection	15,537	2.89
Breast resection	15,431	2.87
Cesarean section	40,807	7.60
Cardioverter - defibrillator implantation	9,816	1.83
Catheter ablation – complex	9,786	1.82
Closure of the defect with a skin flap	18,869	3.52
Complex arthroscopy	33,781	6.29
Endarterectomy	6,859	1.28
Extra-anatomical lung resection	2,337	0.44
Gastrectomy	1,697	0.32
Hernia - adults	31,487	5.87
Hernia - children 3-15 years	5,406	1.01
Hernia - children under 3 years	2,824	0.53
Laparoscopic cholecystectomy	17,430	3.25
Nephrectomy	7,887	1.47
Open cholecystectomy	4,828	0.90
Pacemaker implantation	19,085	3.56
Parathyroid tumour removal	1,776	0.33
PTA	20,042	3.73
PTCA	45,156	8.41
Reconstructive arthroscopy	15,194	2.83
Superficial limb vein surgery	12,249	2.28
Thyroidectomy	14,357	2.67
Tonsillectomy	12,126	2.26
Total hip replacement	12,154	2.26
Total joint replacement in the upper extremity	1,162	0.22
Total knee replacement	8,449	1.57
Transurethral prostatectomy	6,694	1.25
Transurethral resection of bladder tumour	14,327	2.67
Vaginal delivery	113,334	21.11
Valve replacement	757	0.14

Table A.4: LOS models: Marginal effects

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Year of discharge						
(base = year 2015)						
year 2016	-0.049*	-0.041	-0.104**	-0.025	-0.091	0.503***
	(0.030)	(0.030)	(0.043)	(0.072)	(0.065)	(0.154)
year 2017	-0.155***	-0.141***	-0.226***	-0.218**	-0.236***	0.035
	(0.039)	(0.037)	(0.055)	(0.087)	(0.087)	(0.167)
year 2018	-0.267***	-0.254***	-0.343***	-0.420***	-0.402***	-0.215*
	(0.045)	(0.057)	(0.052)	(0.091)	(0.090)	(0.115)
year 2019	-0.323***	-0.327***	-0.368***	-0.383***	-0.391***	-0.131
	(0.045)	(0.054)	(0.067)	(0.088)	(0.081)	(0.214)
Age						
(base = DEC 02-04)						
DEC 01	-0.200	-0.143	-0.640***	-0.053	0.065	-0.810*
	(0.131)	(0.120)	(0.172)	(0.374)	(0.450)	(0.446)
DEC 05	-0.040	-0.051	0.007	-0.091	-0.077	0.107
	(0.054)	(0.060)	(0.055)	(0.065)	(0.047)	(0.150)
DEC 06	0.055	0.055	0.090	-0.112	-0.111	0.338*
	(0.092)	(0.096)	(0.108)	(0.093)	(0.074)	(0.202)
DEC 07	0.177	0.168	0.248*	-0.018	0.008	0.540**
	(0.111)	(0.110)	(0.136)	(0.099)	(0.076)	(0.216)
DEC 08	0.405***	0.393***	0.484***	0.240**	0.277***	0.844***
	(0.116)	(0.110)	(0.158)	(0.107)	(0.094)	(0.228)
DEC 09-10	0.764***	0.761***	0.818***	0.703***	0.792***	1.014***
	(0.169)	(0.166)	(0.198)	(0.154)	(0.182)	(0.178)
Gender						
(base = male)						
female	0.066	0.092	-0.007	0.026	0.098	-0.026
	(0.064)	(0.067)	(0.059)	(0.072)	(0.067)	(0.097)
CC level						
(base = without CC)						
with CC	0.888***	0.870***	0.938***	-	-	-
	(0.162)	(0.165)	(0.154)			
with MCC	2.557***	2.490***	2.785***	-	-	-
	(0.321)	(0.303)	(0.385)			
without split	1.802	1.604	2.540**	-	-	-
	(1.291)	(1.313)	(1.221)			
ICU						
(base = no)						
ICU (yes)	1.630***	1.672***	1.497***	2.458***	2.038***	3.714***
	(0.403)	(0.402)	(0.462)	(0.465)	(0.396)	(0.567)

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Continuation of Table A.4

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Hospital effects	included	included	included	included	included	included
Episode of care effects	included	included	included	included	included	included
Observations	536,782	392,728	144,054	420,462	92,337	21,764
Model	ZTNB	ZTNB	ZTNB	ZT Poisson	ZTNB	ZTNB
Pseudo R-squared	0.164	0.163	0.172	0.166	0.144	0.142

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.5: LOS models: Incidence rate ratios

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Year of discharge						
(base = year 2015)						
year 2016	0.991*	0.993	0.980**	0.986**	0.987	1.050***
	(0.005)	(0.005)	(0.008)	(0.005)	(0.010)	(0.016)
year 2017	0.971***	0.974***	0.956***	0.972***	0.965***	1.003
	(0.007)	(0.007)	(0.010)	(0.006)	(0.013)	(0.017)
year 2018	0.951***	0.954***	0.933***	0.951***	0.940***	0.979*
	(0.008)	(0.010)	(0.010)	(0.007)	(0.013)	(0.011)
year 2019	0.940***	0.941***	0.928***	0.934***	0.942***	0.987
	(0.008)	(0.010)	(0.013)	(0.007)	(0.012)	(0.021)
Age						
(base = DEC 02-04)						
DEC 01	0.961	0.973	0.864***	0.947**	1.010	0.916*
	(0.026)	(0.023)	(0.037)	(0.021)	(0.070)	(0.045)
DEC 05	0.992	0.990	1.001	0.995	0.988	1.011
	(0.011)	(0.011)	(0.012)	(0.012)	(0.007)	(0.016)
DEC 06	1.011	1.010	1.019	1.019	0.983	1.035*
	(0.018)	(0.018)	(0.023)	(0.022)	(0.011)	(0.021)
DEC 07	1.035	1.032	1.053*	1.043*	1.001	1.056**
	(0.022)	(0.021)	(0.030)	(0.027)	(0.012)	(0.023)
DEC 08	1.079***	1.075***	1.103***	1.087***	1.043***	1.087***
	(0.024)	(0.022)	(0.035)	(0.029)	(0.015)	(0.025)
DEC 09-10	1.150***	1.145***	1.174***	1.148***	1.124***	1.105***
	(0.035)	(0.033)	(0.045)	(0.039)	(0.029)	(0.019)
Gender						
(base = male)						
female	1.013	1.017	0.999	1.015	1.015	0.997
	(0.012)	(0.013)	(0.012)	(0.015)	(0.010)	(0.010)
CC level						
(base = without CC)						
with CC	1.178***	1.170***	1.201***	-	-	-
	(0.034)	(0.034)	(0.035)			
with MCC	1.512***	1.487***	1.596***	-	-	-
	(0.070)	(0.064)	(0.089)			
without split	1.361	1.314	1.544**	-	-	-
	(0.259)	(0.257)	(0.262)			
ICU						
(base = no)						
ICU (yes)	1.336***	1.338***	1.327***	1.321***	1.354***	1.472***
	(0.091)	(0.089)	(0.109)	(0.093)	(0.078)	(0.093)

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Continuation of Table A.5

	(1) Full sample	(2) Large	(3) Medium-sized	(4) Without CC	(5) With CC	(6) With MCC
Hospital effects	included	included	included	included	included	included
Episode of care effects	included	included	included	included	included	included
Observations	536,782	392,728	144,054	420,462	92,337	21,764
Model	ZTNB	ZTNB	ZTNB	ZT Poisson	ZTNB	ZTNB
alpha	0.013***	0.016***	0.002***	-	0.041***	0.116***
	(0.016)	(0.017)	(0.001)		(0.020)	(0.021)
Pseudo R-squared	0.164	0.163	0.172	0.166	0.144	0.142

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.6: LOS models by episodes of care: Marginal effects

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Year of discharge *(base = year 2015)*					
year 2016	-0.122	-0.162	-0.017	-0.273	-0.013
	(0.078)	(0.229)	(0.064)	(0.248)	(0.049)
year 2017	-0.190*	-0.401	-0.017	-0.507	-0.072
	(0.111)	(0.276)	(0.086)	(0.330)	(0.058)
year 2018	-0.237***	-0.827**	-0.310***	-0.732**	-0.121***
	(0.091)	(0.345)	(0.064)	(0.357)	(0.043)
year 2019	-0.298***	-1.237***	-0.359***	-0.988***	-0.197***
	(0.088)	(0.255)	(0.079)	(0.298)	(0.048)
Age					
DEC 01	0.276*	1.259	-	-	-
	(0.160)	(1.117)			
DEC 02-04	base	base	-	-	-
	(.)	(.)			
DEC 05	-0.023	-0.131	-	-	-
	(0.039)	(0.462)			
DEC 06	0.034	-0.027	-	-	-
	(0.041)	(0.416)			
DEC 07	0.239***	0.408	-	-	-
	(0.046)	(0.404)			
DEC 08	0.561***	0.923*	-	-	-
	(0.064)	(0.495)			
DEC 09-10	1.019***	2.305***	-	-	-
	(0.109)	(0.493)			
DEC 01-05	-	-	base	base	-
			(.)	(.)	
DEC06	-	-	0.017	-0.027	-
			(0.035)	(0.162)	
DEC07	-	-	0.182***	0.243**	-
			(0.028)	(0.109)	
DEC08	-	-	0.436***	0.678***	-
			(0.039)	(0.144)	
DEC 09-10	-	-	1.006***	1.258***	-
			(0.084)	(0.171)	
DEC02	-	-	-	-	base
					(.)
DEC03	-	-	-	-	-0.011
					(0.038)

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Continuation of Table A.6

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
DEC04	-	-	-	-	-0.051 (0.037)
DEC05	-	-	-	-	-0.012 (0.041)
Gender *(base = male)*					
female	-0.160*** (0.037)	0.008 (0.156)	0.082** (0.034)	0.099 (0.064)	-
CC level *(base = without CC)*					
with CC	0.642** (0.279)	3.865*** (0.399)	1.162*** (0.168)	0.809*** (0.167)	0.472*** (0.062)
with MCC	1.636*** (0.170)	9.785*** (0.426)	1.957*** (0.111)	2.174*** (0.359)	0.752*** (0.131)
without split	-	26.260*** (1.424)	3.254*** (0.419)	-	0.182 (0.141)
ICU *(base = no)*					
ICU (yes)	1.553*** (0.189)	2.818*** (0.372)	2.841*** (0.268)	0.578*** (0.102)	0.284 (0.196)
Additional variable *(base = Vaginal delivery)*					
Cesarean section	-	-	-	-	1.326*** (0.186)
Hospital effects	included	included	included	included	included
Observations	17,430	15,537	45,156	12,154	154,141
Model	ZT Poisson	ZTNB	ZTNB	ZT Poisson	ZT Poisson
Pseudo R-squared	0.038	0.057	0.113	0.033	0.027

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.7: LOS models by episodes of care: Incidence rate ratios

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
Year of discharge *(base = year 2015)*					
year 2016	0.977	0.989	0.996	0.976	0.997
	(0.015)	(0.015)	(0.017)	(0.021)	(0.009)
year 2017	0.964*	0.974	0.996	0.956	0.986
	(0.021)	(0.018)	(0.022)	(0.028)	(0.011)
year 2018	0.955***	0.946**	0.919***	0.937**	0.977***
	(0.017)	(0.022)	(0.016)	(0.030)	(0.008)
year 2019	0.943***	0.919***	0.906***	0.914***	0.962***
	(0.016)	(0.016)	(0.019)	(0.024)	(0.009)
Age					
DEC01	1.056*	1.089	-	-	-
	(0.032)	(0.080)			
DEC 02-04	base	base	-	-	-
	(.)	(.)			
DEC 05	0.995	0.991	-	-	-
	(0.008)	(0.032)			
DEC 06	1.007	0.998	-	-	-
	(0.008)	(0.029)			
DEC 07	1.049***	1.029	-	-	-
	(0.010)	(0.029)			
DEC 08	1.114***	1.065*	-	-	-
	(0.014)	(0.037)			
DEC 09-10	1.207***	1.163***	-	-	-
	(0.023)	(0.039)			
DEC 01-05	-	-	base	base	-
			(.)	(.)	
DEC06	-	-	1.005	0.997	-
			(0.010)	(0.015)	
DEC07	-	-	1.054***	1.023**	-
			(0.009)	(0.011)	
DEC08	-	-	1.130***	1.064***	-
			(0.012)	(0.014)	
DEC 09-10	-	-	1.299***	1.119***	-
			(0.028)	(0.017)	
DEC02	-	-	-	-	base
					(.)
DEC03	-	-	-	-	0.998
					(0.007)

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Continuation of Table A.7

	(1) Laparoscopic cholecystectomy	(2) Bowel resection	(3) PTCA	(4) Hip replacement	(5) Delivery
DEC04	-	-	-	-	0.990 (0.007)
DEC05	-	-	-	-	0.998 (0.008)
Gender *(base = male)*					
female	0.969*** (0.007)	1.001 (0.011)	1.022** (0.009)	1.009 (0.006)	-
CC level *(base = without CC)*					
with CC	1.129** (0.057)	1.328*** (0.038)	1.347*** (0.054)	1.075*** (0.016)	1.094*** (0.013)
with MCC	1.330*** (0.036)	1.831*** (0.046)	1.585*** (0.039)	1.201*** (0.033)	1.150*** (0.026)
without split	-	3.230*** (0.123)	1.972*** (0.130)	-	1.036 (0.028)
ICU *(base = no)*					
ICU (yes)	1.316*** (0.040)	1.230*** (0.037)	1.964*** (0.118)	1.055*** (0.010)	1.056 (0.039)
Additional variable *(base = Vaginal delivery)*					
Cesarean section	-	-	-	-	1.276*** (0.025)
Hospital effects	included	included	included	included	included
Observations	17,430	15,537	45,156	12,154	154,141
Model	ZT Poisson	ZTNB	ZTNB	ZT Poisson	ZT Poisson
alpha	-	0.108*** (0.007)	0.057*** (0.014)	-	-
Pseudo R-squared	0.038	0.057	0.113	0.033	0.027

Note: Length of stay is a dependent variable, robust standard errors are provided in parentheses; *p<0.1; **p<0.05; ***p<0.01.