Universität Augsburg University

Essays in case mix planning

Kumulative Dissertation

der Wirtschaftswissenschaftlichen Fakultät

der Universität Augsburg

zur Erlangung des Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

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Datum der mündlichen Prüfung: 19.11.2018

List of contributions

This dissertation contains the following contributions published in or submitted to scientific journals. The specified categories relate to the journal ranking JOURQUAL 3 of the Verband der Hochschullehrer für Betriebswirtschaft e.V. [22]. The order of the contributions corresponds to the order of print in this dissertation.

Contribution 1

Hof, S., Fügener, A., Schoenfelder, J., Brunner, J. O., 2017. Case mix planning in hospitals: a review and future agenda. Health Care Management Science 20, 207-220.
The final authenticated version is available online at:
https://doi.org/10.1007/s10729-015-9342-2

Status: published in Health Care Management Science, category A.

Contribution 2

McRae, S., 2018. Long-term forecasting of regional demand for hospital services.

Status: submitted to Operations Research for Healthcare, unranked. Date of submission: June 4, 2020.

Contribution 3

McRae, S., Brunner, J. O., Bard, J. F., 2020. Analyzing economies of scale and scope in hospitals by use of case mix planning. Health Care Management Science 23, 80-101.
The final authenticated version is available online at:
https://doi.org/10.1007/s10729-019-09476-2

Status: published in Health Care Management Science, category A.

Contribution 4

McRae, S., Brunner, J. O., 2020. Assessing the impact of uncertainty and the level of aggregation in case mix planning. Omega 97, 102086.
The final authenticated version is available online at:
https://doi.org/10.1016/j.omega.2019.07.002

Status: published online in Omega, category B.

Acknowledgements

First and foremost I am grateful for the person bringing sunshine to my life which is so bright that even the darkest winter nights appear as sparkling wonders to me! Thank you my beloved wife Amanda for always being there to support me and showing me how special life can be! Additional gratitude goes to our daughter for spreading joy and smiles everywhere she goes!

Special gratitude goes to my academic advisor, Prof. Dr. Jens O. Brunner, thank you for the infinite patience and the confidence you have shown in me. In addition I want to thank Jan Schoenfelder and Andreas Fügener for providing academical guidance and for stimulating discussions and all colleagues of the UNIKA-T for the wonderful time I had during my PhD studies.

I am grateful for the support of my parents, siblings, their plus ones, and the Mc-Crazy-in-laws and for always being there to support me and fuel my ambitions. A special gratitude goes to all power-nannys supporting us! An honorable mention goes to the jelly bear waving in the belly.

Thank you all for your support!

Contents

1 Introduction

The provision of hospital services is in area of tension between responsively providing services at a high quality and a fair funding of such services at affordable costs. The efficient use of available resources can help to fulfill both goals simultaneously. The German version of the Diagnosis Related Group (DRG) reimbursement system was introduced in 2003. The introduction followed an international trend to case-based payment systems in which hospitals are reimbursed according to the number of patients. One intention of the introduction was to set incentives for a more efficient treatment of patients [6]. The case of German hospitals is regularly used in the remainder of this dissertation to motivate the contributions. However, most issues can be transferred to a variety of similar health systems.

Figure 1 illustrates the development of inpatient days in German hospitals over ten years from 2007 to 2016 using data provided by the German Federal Statistical Office [21]. The first plot shows that the average length of hospital stays decreased considerably in the aftermath of the introduction of the DRG system. This reduction can be attributed to some extent to the above mentioned incentives. However, case-based payment systems also give rise to misguided incentives to inflate patient volumes beyond what is necessary since the patient volumes directly relate to the revenue of hospitals [5]. The trend of increasing inpatient volumes is depicted in the second plot. This trend can only be partially explained by the demographic change. The product of the length of stay and the patient volume is illustrated in the third plot. The number of inpatient days remains almost constant between 2007 and 2016. This example illustrates some of the challenges decision makers in charge of controlling reimbursement systems face. As will be seen in the remainder of this dissertation, the tool of case mix planning, as defined in Section 1.2, can provide support to identify and quantify improvement potentials for reimbursement systems.

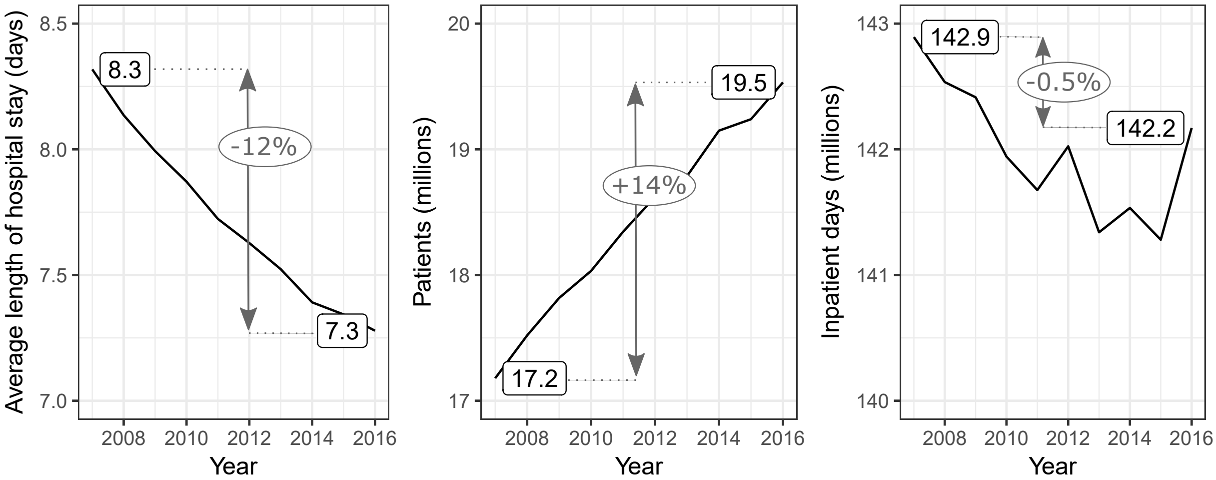

Figure 1 Development of inpatient days in German hospitals

1.1 Introductory example

The following example of different types of hospitals in a German region serves as a motivation for the in-depth analysis of strategies for case mix planning carried out in this thesis. In the region under consideration, there is one large city with 290,000 inhabitants surrounded by smaller cities and local communities summing up to a total of approximately 500,000 inhabitants. The International Statistical Classification of Diseases and Related Health Problems (ICD) is used to describe the case mix. The ICD codes are truncated after the first character (ICD1 code). These ICD1 codes largely correspond to Major Diagnostic Categories (MDC). Figure 2 illustrates the current case mix of the nine hospitals. This mosaic plot is to be read as follows. Each rectangle represents a combination of a hospital with an ICD1 code. The width of the rectangle represents the total share of patients of the respective hospital of all 110,000 inpatients per year served by the nine hospitals. The height of the rectangle represents the share of this ICD1 code relative to the total volume of patients in this hospital. The sum of the heights is equal to 1 for each hospital. Consequently, the area of each rectangle is proportional to the number of patients of the ICD1 category served by the hospital.

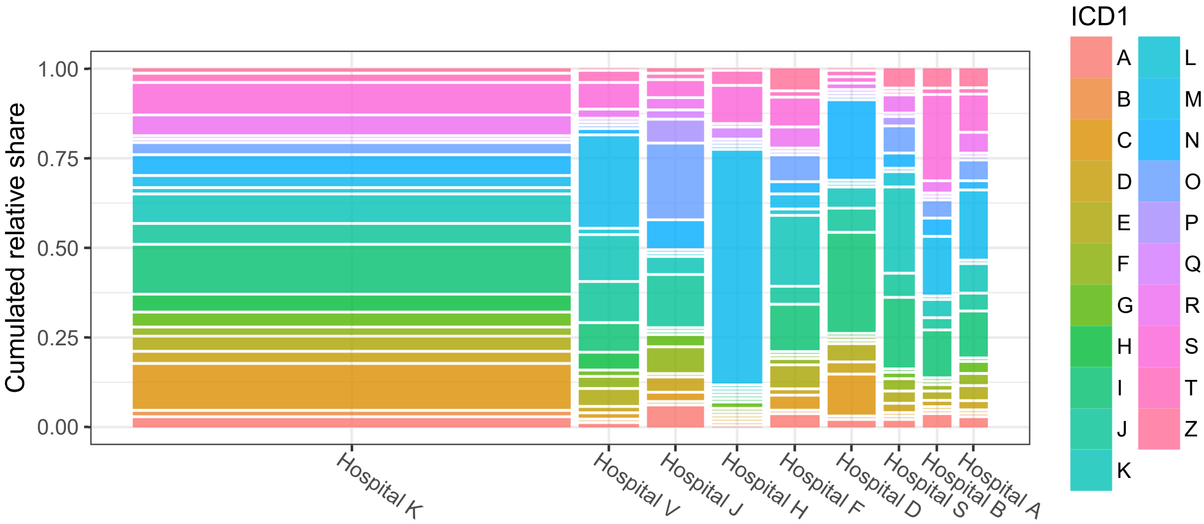

Figure 2 Case mix of hospitals in German region

Hospital K, the largest hospital in this region, serves more patients than all other hospitals together. The Gini coefficient is a measure describing inequalities. The value of this coefficient is between 0 and 1. A Gini coefficient of 0 for a hospital represents the case where an equal number of patients is treated from each ICD1 category in this hospital. The other extreme, a Gini coefficient of 1, represents a situation where all patients of a hospital are patients from the same ICD1 category. The Gini coefficient can thus be seen as a measure of the degree of specialization of a hospital. The Gini coefficients of the nine hospitals are reported in Table 1.

Table 1 Gini coefficients of hospitals

Hospital	K	V	J	H	F	D	S	B	A
Gini coefficient	0.47	0.67	0.62	0.92	0.58	0.78	0.67	0.68	0.59
Urban (u)/rural (r)	u	u	u	u	r	u	r	r	r

Hospital K has a Gini coefficient of 0.47. In comparison to the other hospitals, it provides the broadest range of services and its case mix is balanced. The broad range partially stems from legal service obligations due to the maximum level of care this hospital is obliged to offer. The Gini coefficients of all other hospitals located in the largest city, indicated by “u”, are larger than 0.62, indicating the need for differentiation by specializing on a subset of ICD1 categories in urban areas. The largest Gini coefficient of 0.92 is achieved by Hospital H which corresponds to the graphical impression of Figure

2. This hospital is highly specialized in treatments attributed to ICD1 category M which corresponds to the MDC "Diseases and Disorders of the Musculoskeletal System And Connective Tissue". The hospitals F and A are located in small cities in the peripheral region of the large city. They provide a broader range of services to attract the local population. Hospitals S and B constitute a hospital network and are also located in the peripheral region. However, they locally aggregate the treatment of patients according to the diseases of the patients resulting in a higher degree of specialization of the two sites. This example illustrates that different situations can necessitate different case mix strategies and that there is no dominant strategy which fits for all hospitals. The goal of this thesis is to identify driving factors for hospital case mix planning.

1.2 Definition of the case mix planning problem and research questions

There are several strategies for profit orientated but also for non-profit hospitals to react to economic pressure in case-based payment systems. Roughly speaking, the profit of a hospital is determined by the following equation.

$$\mathit{profit} = \sum_{d \in DRG} \mathit{volume}_d \cdot (\mathit{case\ reimbursement}_d - \mathit{variable\ costs}_d) - \mathit{fixed\ costs} \tag{1}$$

In case-based payment systems, the revenue generated by a single patient is constituted by a fixed reimbursement related to the DRG a patient is assigned to. In the German DRG system, this amount is determined multiplying a relative case weight with a base value [19]. These payments are adjusted only to a minor degree under certain circumstances. Consequently, the only relevant strategy for hospitals related to pricing is to use their margin for interpretation in order to assign patients to DRGs with higher case weights. This margin for interpretation decreases with increasing accuracy of DRG grouping procedures [5] and can thus be assumed to be neglectable in advanced DRG systems.

Increasing profit by cutting variable and fixed costs via efficiency increases is the first major strategy. Cost cutting strategies are highly relevant to control costs in the healthcare industry [2]. However, cost reductions are limited to a certain extent. Justified resistance against such management strategies can arise among medical staff and patients when patient safety or quality of care are affected.

The second major strategy for improving profit is to increase patient volumes. This strategy is promising when assuming a high share of fixed costs. However, costs often deemed to be fixed in hospitals, such as staffing costs, can in fact be influenced by management, e.g., on an annual basis, and are thus not inherently fixed [13]. A situation where all or a majority of the hospitals follow such a strategy of increasing patient volumes is only beneficial from an economic perspective if the demand exceeds the available supply such as in the case of long waiting lists for surgeries. Artificial increases of patient volumes that go beyond medical requirements should be avoided since they induce unnecessary costs for the health system and can harm patients in the worst case. In general, this strategy is limited by the total available demand for health services.

The two strategies of increasing efficiency and increasing the volume are already brought up in the beginning of the introduction. The third major strategy is a modification of the second strategy. Instead of increasing the total number of patients, a focus is set on patients that can be treated efficiently in the respective hospital since this results in high contribution margins. The rough resource structure and the patient demand are two restricting factors that should be considered when pursuing this strategy.

The resulting planning problem is referred to as the case mix planning problem. The aim of this problem is to determine the optimal mix and volume of patients subject to resource constraints and patient demand. Analyzing the strategic tool of case mix planning is the driving motivation for the essays summarized in the next section. In particular, the goal of the thesis is to find answers for the following research questions:

Research question 1: What aspects of case mix planning for hospitals are covered in the literature and what are promising areas for future research?

Research question 2: How can long-term demand be estimated required as input for case mix planning?

Research question 3: Can case mix planning be used to identify impacts of economies of scale and scope on the optimal case mix of a hospital?

Research question 4: What complicating aspects should be considered when planning the case mix? What is a convenient level of aggregation?

1.3 Contents of the thesis

The remainder of the thesis is structured as follows. In Section 2, the four contributions are summarized. The full version of these papers is attached in the appendix. The contributions of the dissertation are discussed in Section 3. This discussion includes a summary of the findings, an enumeration of improvement potentials for the German DRG system, and the description of possible future research directions. A conclusion is drawn in Section 4.

2 Summary of the contributions

In this section, a summary of the individual contributions to the literature is provided. All contributions are attached in the appendix.

2.1 Case mix planning in hospitals: a review and future agenda

Hof et al. [11] review literature on case mix planning problems and identify an agenda for future research. The main contribution of the paper is to provide the first literature review focusing on case mix planning. After identifying the role of case mix planning in hospital demand and capacity planning, case mix planning problems described in the literature are classified according to methodological aspects. Subsequently, the transition from theoretical research to application in practice is discussed. Concluding, an agenda for future research is developed.

Case mix planning can be considered as a tool for strategic resource capacity planning in hospitals. The case mix planning problem is strongly interrelated with the strategic allocation of resources. It is also directly linked to capacity dimensioning and downstream resource planning and scheduling problems. The literature review comprises 25 publications on case mix planning up to 2015. Since the first publication on the case mix planning problem in 1963, the frequency of publications on case mix planning has since increased and especially gained importance in the last ten years corresponding to the establishment of case payment systems in most western countries. In such systems, hospitals have an incentive to actively manage their case mix since the revenue of a hospital is directly related to the number of patients from the different DRGs.

The core of the review is a description of the state of the art in case mix planning. There are two basic approaches to case mix planning described in the literature. The first focuses on determining target volumes for patient admissions and the second on identifying a resource allocation scheme inducing the desired mix of patients. The latter is mostly used when the operating theater is considered as the predominant major scarce hospital resource. Case mix planning can be used for a variety of purposes, including strategic portfolio planning, strategic resource planning, financial planning, the assessment of future investment options, and the evaluation of reimbursement systems.

The mathematical methods used in the literature range from linear programs to non-linear mixed integer programs. Most of the non-linear formulations stem from the incorporation of stochastic aspects. Uncertainties in the case mix planning problem can be clustered into uncertainties related to demand, to the variability in resource consumption, to supply, and to objective function coefficients. Uncertainty of demand is considered in several publications whereas other types of uncertainties are only addressed in few approaches.

Goals in case mix planning predominantly relate to financial goals such as maximizing the profit or the revenue which is not surprising due to financial incentives associated with DRGs in case payment systems. Non-financial goals described in the literature include aspects relating to the waiting time of patients or the quality of treatment. Patients are grouped according to their diagnosis, to an organizational unit within a hospital they are assigned to, to their resource requirements or to their payer. While DRGs are a natural choice to group patients in DRG-based reimbursement systems, it can make sense to opt for other classifications, e.g., if it is difficult to control patient volumes on such a detailed level. The length of the planning horizon is typically one year. The most common approaches are to either decide on aggregated volumes for the whole year or to define weekly patterns which are repeated cyclically throughout the year. The operating rooms are often considered as the most scarce resource within a hospital. Therefore, operating room capacity is modeled in most papers on case mix planning as a factor constraining the case mix. Besides operating room capacity, a variety of other factors such as beds, physicians, nurses, capacity of the intensive care unit, and diagnostic services are assumed to potentially restrict the case mix. Patient demand is considered in almost all publications as a constraining factor which is an indicator for the sensitivity of the objective value to changes in demand.

Under certain external circumstances, it can be difficult to control the case mix of a hospital. However, in general, the desired case mix can be influenced via various channels. Resource allocation, waiting list management, relationships to primary care providers, and marketing can be used to influence the case mix. Modern hospital information systems provide most of the data needed as input for case mix planning. The precise assignment of fixed costs such as personnel costs to individual patients is essential if the maximization of profit is the primary objective since variable costs such as costs for drugs or dressing materials only account for a small share of occurring costs. Resource requirements of patients can be estimated from historical data. Operational inefficiencies, e.g., due to fluctuations of supply and demand, have to be taken into account when estimating the supply of resources in aggregated planning approaches in order to not overestimate the available supply. Due to the sensitivity of the model output to demand constraints, considerable effort should be invested in estimating the demand. This is often challenging since the true demand for hospital services is likely to exceed historic patient volumes recorded by hospital information systems. Almost all papers considered in the review make use of computational studies. While in a majority of the papers real data is used, an usage in practice of the proposed methods is only documented in three of the 25 papers.

Concluding, case mix planning is a valuable tool for supporting strategic decisions on the case mix and on hospital resource planning. It can be used to analyze complex relations between demand, supply, and financial performance indicators in general, but also to weigh specific strategic options against each other. In order to obtain sound decisions, the output of case mix planning has to be set into relation with the output of other related planning problems and be discussed with all involved key stakeholders. Case mix planning is still considered only scarcely in the literature but can be expected to gain increasing importance especially in environments with increasing economic pressure on hospitals.

2.2 Long-term forecasting of regional demand for hospital services

Long-term forecasting of patient demand is crucial for deriving sustainable case mix strategies since major alterations of the case mix are often linked to long-term investments. In the literature on operations research in health care, demand estimations are often based on historic admitted patient volumes. Such estimations often neglect the demand which is not met since information on the number of patients that are turned away is seldom recorded in hospital information systems. In addition, the number of patients choosing treatment in competing hospitals is often unknown. Further, demographic changes and medical development should be included in demand forecasts to provide precise estimates of future demand.

The contribution of this paper is to present a structured method for forecasting the regional demand for hospital services for long-term planning horizons. Life expectancy is steadily increasing in most countries. The highest share of hospital care is required by the group of elderly people. There is a vivid discussion in the literature on whether increases in life expectancy rather entail additional life years spent in poor health or whether the stadium of poor health is postponed to later years of life. The current major consensus is that different disease categories exhibit qualitatively differing trends.

The proposed method for forecasting patient demand consists of three steps. In the first step, the population of the region under consideration is forecasted. In the second step, incidence rates are projected for different age and sex groups. These two forecasts are used to derive estimates for future demand for inpatient services in the third step.

Population forecasts are well studied in the literature. Given stable birth, death, and migration rates, population forecasts can be expected to be of high accuracy. Birth rates are only relevant to a larger extent for hospital stays related to birth. Since a majority of hospital costs is generated by the age groups of 50 years and higher, birth rates are only of minor relevance for hospital stays related to other types of diseases assuming forecasting horizons of less than 50 years. Life expectancy and consequently mortality show stable trends in most developed countries. Thus, migration is the only factor imposing a major challenge for forecasting the relevant population of older age groups accounting for the majority of hospital demand.

Forecasting incidence rates is a complex issue since different disease categories show different trends. In addition, incidence rates are influenced by a variety of factors such as sociological trends, medical trends, or even legal directives. Different regression and autoregressive integrated moving average (ARIMA) models are potential candidates for forecasting disease rates for each age and sex group. The best forecast for each combination and different forecasting horizons is identified using rolling forecasting origins. The method is applied to real data of a German city with a population of 0.3 million people. Since the number of historic observations for each disease, age, and sex group is limited, models with a limited number of parameters outperform complicated forecasting methods since the latter are prone to overfitting. The suggested forecasting procedure provides precise estimates when evaluated with the given test data. Future patient demand is estimated multiplying the forecasted population with the projected disease rates for each year of the forecasting horizon. Summarizing, the proposed procedure provides good estimates for future demand for inpatient services which can be used as input for a variety of hospital planning problems such as case mix planning.

2.3 Analyzing economies of scale and scope in hospitals by use of case mix planning

Empiric studies on economies of scale and scope in hospitals provide ambiguous results. Thus, a non-convex optimization problem is suggested to analyze potential effects of changes in the efficiency of resource consumption and potential effects of spreading fixed costs over a greater number of patients on the optimal case mix of a hospital. An iterative solution procedure using piecewise linear functions to derive lower and upper bounds converging to the optimal solution is developed.

Seemingly contradictory results can be found in the literature on economies of scale and scope in hospitals. On a closer look, these discrepancies often stem from different contexts and assumptions. The quantitative but also qualitative variation of the results is also an indicator for the complexity of the provision of hospital services. From a hospital resource planning perspective, the optimal case mix for a hospital can be analyzed adapting the product mix problem known from production planning in manufacturing to the contexts of hospitals. Literature on case mix planning problems has focused on linear and mixed integer linear programming models where the relation of patients to required resources for their treatment is simplified to a linear relationship neglecting efficiency increases or decreases with increasing scale.

The problem described in this paper is used to determine the optimal case mix of a hospital considering changes in the efficiency of resource consumption with increasing scale. The planning horizon of the problem is one year. Additional features of the model which have not been discussed in previous literature on case mix planning are resource reallocations coming at certain costs and the incorporation of policy constraints restricting the volume of patients weighted by their DRG-weights and the average DRG-weight of the optimal case mix. The problem is modeled as a non-linear mixed integer program.

Due to the generic formulation of the problem with resource consumption relations which are not necessarily linear or convex, the problem cannot be solved using standard software. Instead, an iterative solution approach making use of lower and upper bounds converging to the optimal solution is formulated. Lower bounds are identified using piecewise linear functions overestimating the resource requirements and upper bounds using piecewise linear functions underestimating the resource requirements. These piecewise functions are not necessarily continuous. The approach followed in this paper for the construction of piecewise linear functions is to use a combination of first order Taylor approximations and interpolations between breakpoints.

The number of breakpoints which is necessary to solve the problem to a given accuracy is in general not known in advance. Traditional approaches on linear approximations for non-linear mixed integer programs focus on escalating the number of breakpoints until the desired accuracy is met. As an alternative, the novel idea of shifting the breakpoints in the course of the algorithm is introduced. The essential underlying observation is that using the patient volumes of the optimal solution of the previous iteration as breakpoints when identifying lower bounds generates a feasible solution for the problem of the next iteration which is at least as good as the optimal solution of the previous iteration. Thus, the lower bound potentially increases with each iteration unless the solution procedure gets stuck in a local optimum. In this case, increases in the number of breakpoints are necessary to guarantee global convergence of the algorithm.

The solution procedure is applied to data of 1,456 German hospitals. Different types of functions with respect to the curvature are defined describing the relations between patient volume and required resources for treatment since the relations can vary qualitatively between different hospital settings. The proposed algorithm is evaluated for the different types of functions. The computational results show that all instances could be solved with the proposed solution procedure. Following the evaluation of the algorithm, the output of the model for one hospital is presented to reveal potential use cases. Sensitivity analyses show that the case mix is highly sensitive to patient bounds. In addition, it is illustrated that the dependencies between patient volumes and resource requirements should be well studied to enable a sound choice of case mix targets.

Summarizing, an approach for evaluating the impact of economies of scale and scope on the optimal case mix of a hospital is presented. Economies of scale and scope can be exploited best when the scope for decision-making concerning the case mix is wide. Thus, the case mix planning approach discussed in this paper is of particular relevance for decision makers considering major changes in resource structure and case mix of their hospital as is the case when restructuring a hospital. From a mathematical point of view, a solution procedure is presented which helps to solve extensive non-linear problems that cannot be solved with standard software. The procedure makes use of the novel idea of shifting breakpoints when using piecewise linear approximations instead of solely increasing the number of breakpoints.

2.4 Assessing the impact of uncertainty and the level of aggregation in case mix planning

Case mix planning is usually considered as the first phase of a cyclic planning approach to hospital resource planning. Simultaneously including all downstream planning problems when planning the case mix is impossible from a computational perspective due to the highly complex nature of the provision of inpatient care and a variety of stochastic influences. Different methods integrating some complicating aspects into the case mix planning problem are discussed in the literature. However, it is not clear which aspects actually add value when being considered in case mix planning and which aspects only add complexity without leading to improved results.

The contribution of this paper is to provide a framework for identifying relevant aspects that should be considered when planning the case mix. The framework includes a standardization of the notation used in case mix planning approaches discussed in the literature. A simulation environment is used to evaluate strategies derived by case mix planning. All further relevant aspects are taken into account in the simulation that have not been considered yet in the phase of case mix planning. The aim of the framework is to identify model structures adding the most value.

The standardization of the notation of different case mix planning approaches is used to identify a generic basic problem and different types of model extensions. The first type of extension concerns stochastic demand. Variability in demand is potentially relevant for planning the case mix since buffer capacity has to be reserved to cope with demand peaks of certain patient groups. The second type of extension addresses variability in resource consumption. Similar to stochastic demand, stochastic resource consumption can necessitate buffer capacity. Neglecting variability in resource consumption potentially leads to undesirable mismatches in resource utilization. Such a mismatch can also be the effect of stochastic resource availabilities which can mainly be attributed to stochastic influences on staffing levels. Such effects are addressed in the third type of extension. The last extension concerns the downstream problem of assigning resources to different days such as is the case in admission planning or master surgery scheduling. This extension is potentially relevant if scarce resources include resource types that are required on specified days following the day of surgery. It is common practice in most Western countries to close the operating room on weekends or Sundays for elective surgeries. This habit results in an underutilization of resources such as intensive care unit or regular ward beds during the weekend and on Mondays since no additional elective patients arrive in the wards on days with inactive operating rooms.

The basic case mix planning model is modeled as a mixed integer program. The described extensions are integrated into this planning model using stochastic programming formulations. Sample average approximation is used to solve the resulting stochastic programs. The simulation includes all relevant bottleneck resources and should be fitted to the processes of the individual hospital.

The proposed framework is applied to the problem setting of a large German hospital faced with the task of planning the case mix and allocating resources accordingly for the upcoming year. A factorial study resulting in $2^4 = 16$ case mix planning problems is used to identify the contributions of the different extensions to the operational performance of the hospital. In addition, the accuracy of the solution derived by the case mix planning problems is analyzed. The accuracy is defined by the relative difference between the solution of the case mix planning problem and the simulated value which is determined by using the output of the case mix planning problem as input for the simulation.

Results show that even the most simple case mix planning formulation improves the status quo considerably. The consideration of complicating aspects adds additional value. In particular, the simultaneous consideration of stochastic resource consumption and stochastic resource supply provided satisfying results. Adding the other two extensions improves the performance marginally. The relevance of the individual complicating factors can vary according to the problem setting of the individual hospital. For example, stochastic patient demand might be irrelevant for hospitals with very long waiting lists for surgeries.

The main findings of this contribution are summarized as follows. The most basic case mix formulation adds compelling value when compared to the case mix of the status quo. Integrating complicating extensions improves the outcomes slightly. However, the accuracy of the case mix planning models when compared to simulation outcomes is considerably higher for more detailed models. Thus, hospital managers should be cautious not to set unrealistically high target volumes when using highly aggregated case mix planning models.

3 Discussion of the contributions

In this section, the findings of the four contributions are summarized and discussed. In addition, potential improvements of the German DRG system motivated by the in-depth analysis of case mix planning in this dissertation are presented. Finally, directions for future research are discussed.

3.1 Summary of the findings and limitations

In this subsection, the findings are summarized based on the list of research questions stated in Section 1.2. The contributions are set into context and limitations are identified.

Research question 1: What aspects of case mix planning for hospitals are covered in the literature and what are promising areas for future research?

This research question is addressed with the first contribution summarized in Section 2.1. The first contributions to the literature on case mix planning date back to the 1960s. In these pioneering studies, basic linear programming formulations of the case mix planning problem for hospitals are discussed along with different application scenarios. In the course of the years, the focus shifted from providing a holistic perspective of a hospital to a focus on operating rooms since operating room capacity is mostly considered as the major bottleneck resource in hospitals. However, solely focusing on operating room capacity as a single constraining resource can lead to suboptimal results. Thus, current research aims to consider downstream resources when planning the case mix and connect the case mix planning problem with subsequent planning problems. A second focal point of current research is the integration of stochastic aspects into case mix planning problems. The literature review is focused on operations research and operations management literature. However, it can be valuable to link such problems with findings of other areas such as general management, marketing, or financial planning.

Gaps identified in the first contribution concern economies of scale and scope in case mix planning, stochastic case mix planning, and competition among competing hospitals. The former two gaps are addressed in Section 2.3 and Section 2.4, respectively. Initial ideas for case mix planning in a competitive environment are presented in Section 3.3. Advanced solution methods for case mix planning problems including efficiency changes with increasing scale and possibilities to use case mix planning as a decision support for the design of case-based reimbursement systems are discussed in this section as well.

Research question 2: How can long-term demand be estimated required as input for case mix planning?

Most approaches to estimating demand for hospitals in the operations research and operations management literature are based on historical data. However, such procedures are biased due to two reasons. First, hospital information systems normally only register demand that is actually met. Patients referred to other hospital or patients choosing treatment in other hospitals due to long waiting lists are usually out of the scope of information systems. This is in particular relevant for hospitals competing with other hospitals for patients. Consequently, patient demand is potentially underestimated when solely relying on historical data. The forecasting bias can differ between different patient groups based on the preferences of patients.

A second drawback of using observed patient volumes to determine the future demand concerns the possibility of hospitals to manage admissions such that demand is smoothed. Consequently, the variability of patient demand per time unit is in fact potentially higher than the observed patient volumes per time unit would suggest.

An alternative method to forecast patient volumes is presented in the second contribution described in Section 2.2. This forecast is composed of two projections. The first projection concerns the future population in the catchment area of the hospital which is determined by birth rates, death rates, and migration. Since a majority of hospital visits and occurring costs is generated by people aged 50 or older, birth rates are mainly relevant for departments related to maternity and childbirth. In contrary, life expectancy and death rates are deemed to be a critical factor for future healthcare costs. The population can be assumed to be fairly predictable if the net migration is constant and trends of birth and death rates are stable. The second projection addresses disease rates. Unlike the population, disease rates are in general fare more complicated to predict. This is caused by several factors such as socio-economic trends and medical developments. In addition, the volume of treatment can actively be controlled by healthcare payors and legal restrictions. Different types of diseases exhibit different developments. The forecasting method used in this contribution accounts for this diversity by applying different forecasting methods to different types of diagnosis based on historic patterns. Limitations not covered by this approach concern potential shifts between patients emerging as outpatients and inpatients and changes in the classification of diseases.

Research question 3: Can case mix planning be used to identify impacts of economies of scale and scope on the optimal case mix of a hospital?

Economies of scale and scope are determined by several factors. Some of these aspects can easily be included into case mix planning models while others are considerably more complicated to integrate. The third contribution discussed in Section 2.3 addresses different aspects related to economies of scale and scope.

The impact of changes in the efficiency of resource use with increasing scale is modeled using non-linear functions describing resource requirements. The incorporation of such functions leads to non-linear programs that cannot be solved with off-the-shelf software any more. Thus, a tailored solution methods is developed capable of solving all tested problem instances. The method consists of a piecewise linear approximation with breakpoints that are iteratively shifted in the course of the procedure. To our knowledge, the latter is an entirely new approach. This concept helps to keep the number of breakpoints necessary to obtain an optimal solution considerably low. The possibility of spreading fixed costs is considerably easier to analyze with case mix planning techniques.

Additional innovative components of this case mix planning problem concern penalties on changes in the allocation of resources and the introduction of additional policy constraints. Current case mix planning approaches described in the literature assume that resources can be allocated without any costs within given limits. However, Blake and Carter [4] argue that physicians will only accept alterations of the case mix if the magnitude of changes is small. The proposed policy constraints aim to manage the volume of high-risk patients, the average severity of the diagnoses of the admitted patients, and the hospital case mix as defined by totaling the sum of patients weighted by the relative case weight. The latter may be of particular interest for German hospitals since this weighted sum is the core negotiation issue of the annual negotiations between insurance providers and hospitals.

From a modeling perspective, the approach is limited to modeling efficiencies separately for different patient groups. In addition to such effects, future research could also address crossover effects associated with multiple DRGs. Another limitation concerns the runtimes. This aspect is addressed in Section 3.3. The most complicated instances require several days to be solved with the proposed algorithm. These runtimes can be argued to be acceptable when considering the case mix planning problem as a strategic problem which has only to be solved once a year. However, managers might be interested in analyzing different sets of parameters. It might be worth to analyze whether the technique of column generation can be used to generate better bounds in each iteration of the proposed algorithm.

Research question 4: What complicating aspects should be considered when planning the case mix? What is a convenient level of aggregation?

As indicated in the discussion of research question 1, the analysis of case mix planning problems evolved from simple basic models to more complex models that are considerably more difficult to solve. The fourth contribution of this dissertation, outlined in Section 2.4, provides a framework to evaluate which kinds of complicating aspects add value to case mix planning. Complicating aspects discussed in this contribution concern different types of stochastic influences and artificial variabilities caused by inactive days without elective surgeries during the weekend.

The framework consists of three parts. In the first part, a generic description on modeling case mix planning problems is given. In the second part it is shown how different complicating aspects can be included when planning the case mix. Simulation is used in the third part of the framework to evaluate promising case mix strategies. The latter is an essential part of the model since it provides the possibility to circumvent costly field studies and pilot projects.

Results indicate that the most significant benefits when compared to the status quo can be exploited even with highly aggregated deterministic case mix planning models. The consideration of stochastic aspects adds additional value when planning the case mix. Integrating time-phased aspects to account for variabilities caused by inactive days did not add significant value in the analyzed problem setting in terms of solution quality as evaluated in the simulation. However, time-phased modeling decreased the gap between profits suggested by the case mix planning model and profits that actually can be achieved as determined by the simulation of all relevant processes.

In future research, the decision structure of the problem can be refined to the level of physicians or detailed patient groups such as DRGs. The consideration of dynamic approaches to case mix planning problems is another direction for future research. Stochastic problems are more complicated to solve when compared to their deterministic counterparts due to their non-linear structure. The development of advanced solutions methods is required when the stochastic case mix planning problems are refined as described above. One aspect requiring additional studying concerns the modeling of stochastic resource requirements. Common practice to model stochastic resource requirements is to assume similar representative resource requirements for all patients in a given scenario and multiply the volume of patients with the resulting representative random variable. This leads to an overestimation of variability in resource consumption since the more precise modeling would relate to a manifold convolution of random variables where the number of random variables to be convoluted is a decision variable. This more precise way of modeling induces a highly non-linear problem structure calling for advanced non-linear solution procedures.

3.2 Identified potential for improvement for the German DRG system

In the course of the analysis of different aspects on case mix planning in this dissertation, different drawbacks of the German DRG system emerged. These improvement potentials are not entirely new. However, case mix planning can be used as a tool to quantify these aspects and therefore add valuable insights. Before describing drawbacks of the German DRG system, valuable incentives set by case-based payment systems such as the German DRG system are recalled.

(i) Incentives to treat patients efficiently. Hospitals are reimbursed according to the diagnosis of the patients. Reducing costs by optimizing processes increases the profit.

(ii) Incentives to actively manage the case mix. In urban areas, it is often not necessary to offer a full range of services due to the high density of hospitals. Case mix planning can decrease costs from an economic perspective if patients are treated in hospitals where they can be treated the most efficiently. Assuming that case-based payment rates are based on average costs, no patient groups should be uncared-for in urban areas from a theoretical perspective. In addition, staffing and OR-time overhead can be reduced by effective case mix plans and corresponding allocations. Additional profits can be used to cross-finance other hospital assets.

(iii) Incentives to shut down unprofitable hospitals. Currently, there is an overcapacity

of hospital beds in German hospitals. Since hospitals are reimbursed for patients of a DRG according to average costs, inefficiently operating hospitals cannot survive in the long run leading to a consolidation of the hospital market. The freed capacity can then be reinvested in healthy hospital structures. Case mix planning can be used to estimate the positive and negative impacts of hospital restructuring projects.

Besides these advantages, there are also several drawbacks. Limiting these drawbacks or adding reimbursement components to reduce these downsides is a challenge for policy makers.

(i) Incentives to provide more services than necessary. This is a known problem of case-based reimbursement systems. Control mechanisms such as audits by insurance companies can help to decrease such incentives. Unbundling of treatments between different providers or discharging and readmitting patients are additional behavioral patterns to be controlled for. Misbehavior related to upcoding of DRGs can also be attributed to unjustified means to increase revenue [12].

(ii) Incentives for quality decreases. In a situation where patients cannot assess the quality of treatment, costs for treatments can be decreased in the short term by reducing efforts to provide a high level of quality. This phenomenon also relates to "bloody discharges" where patients are released in unfavorable conditions. Advanced information systems reporting about quality standards from an objective point of view can reduce such incentives. In addition, components depending on quality can be added to the reimbursement of hospitals.

(iii) Missing incentives for providing services in rural areas. Rural areas are characterized by a low density of population. A low population relates to low patient volumes. The provision of hospital services is more attractive in urban areas due to higher patient volumes. Higher patient volumes are advantageous with regard to decreased variability in demand and decreased average fixed costs. The latter is especially true for patient groups involving high shares of fixed costs in reimbursement systems based on average costs. Shutting down hospitals in rural areas as a consequence of consolidation incentives can lead to local undersupply and consequently poses a major threat in terms of insufficient hospital coverage.

(iv) Missing incentives for patient groups involving high risks. Uncertainties necessitate reserve capacities and complicate resource planning. As a consequence, there are incentives to exclude patients involving high uncertainties from the portfolio of services and refer them to other hospitals. Risk-adjusted reimbursement mechanisms can help to compensate for additional resource requirements.

(v) Bias in reimbursements if case weights are solely based on historic costs. Case weights should reflect the economical complexity of patient treatments. In the German DRG system, the cost weights are based on average costs of the year before last. Staffing costs as well as material costs are components influencing treatment costs. If staffing costs increase and material costs decrease steadily, it is beneficial to focus on patient groups with high shares of material costs if case weights are based on historic costs. For example, high shares of material costs arise where orthopedic implants or prosthesis are involved. In the setting described above, orthopedic patients can be assumed to yield attractive profits. However, the described situation would also lead to a global undersupply of patient groups with high shares of staffing costs such as is the case for hospital admissions related to maternity.

Case mix planning can be a valuable tool for hospital providers for defining sound case mix strategies. However, case mix planning approaches can also help to assess the impact of changes in reimbursement systems since case mix planning provides a holistic view on hospital demand and resource planning strategies.

3.3 Future research

The contributions discussed in this dissertation aim to close existing gaps in the literature. However, as indicated by the previous discussion, they only scratch the surface on what can be accomplished with case mix planning. The following three directions for future research can help to refine and extend the presented contributions.

Advanced solution methods for case mix planning problems including changes in the efficiency of resource consumption with increasing scale

The most complex problem instances described in the contribution concerning the relationship between economies of scale and scope and case mix planning which is summarized in Section 2.3 require more than 11 days of runtime for solving the problem to a relative gap between the lower and upper bound on the value of the objective function of 1%. Such solution times are inconvenient for management staff exploring the implications of different parameter settings. More efficient solution methods can help to reduce runtimes. Ma et al. [17] find that column generation can be a promising approach for case mix planning models to decrease solution times. A column generation approach based on a Dantzig-Wolfe-decomposition of the problem described in the contribution discussed in Section 2.3 might be useful to obtain better bounds in the course of the used algorithm.

Case mix planning in a competitive environment

Case mix planning is mostly modeled as an isolated planning problem for a single hospital. As an exception, Rauner et al. [18] use a case mix planning approach to model the allocation of budgets and patients to different cooperating hospitals in an Austrian region. In reality, hospitals often face competition with surrounding hospitals with overlapping catchment areas. Consequently, case mix strategies of different hospitals can interfere with each other. For example, Dexter et al. [8] analyze the effect of patient volumes of one hospital to the patient volumes of another hospital for different specialties.

From a bottom up perspective, a first crucial step to apprehend the impact of case mix strategies of surrounding hospitals on the case mix strategy of a hospital is to understand the process of patients choosing a hospital. In regions with different competing hospitals within convenient travel distance, the travel time as a major factor influencing the hospital choice is often overestimated [8]. General practitioners can play a key role in the choice for a hospital due to their close contact with patients and their significant impact on referrals to hospitals. Cooper et al. [7] notice that general practitioners can observe patient condition before and after surgery and thus can realistically assess the quality of hospital treatment. Perceived quality is another important factor influencing hospital choice. Gooding [9] find that quality concerns are far more important for complicated procedures than for minor issues. The list of different additional factors potentially influencing the selection of a facility for treatment includes personal experience, reputation, waiting time, and recommendations by family members and friends. Results of different studies ranking and weighing such factors depend on the types of factors analyzed, the applied methodology, and external factors such as the hospital system or the cultural background [1, 14, 15, 20].

In case-based lump-sum payment systems, hospitals have an incentive to focus on such patients that can be treated efficiently at the hospital. Besides assessing the importance of different factors for the choice of a hospital, it is crucial to analyze if, how, and to what extent these factors can be influenced. In this regard, it is important to identify the involved stakeholders and their interests.

For example, travel distance can be assumed to be fixed. In contrary, the management of connections with general practitioners can be an important tool to control the case mix of a hospital. Waiting time can be influenced via resource allocation for certain services. Cooper et al. [7] note that quality can be an important differentiating factor for providers in reimbursement systems with fixed prices. Treatment quality can be difficult to be assessed for patients seeking for treatment. Initiatives such as the introduction of obligatory standardized quality reports for German hospitals can increase transparency. Quality orientated reimbursement components are discussed in several countries and impose additional incentives for improving quality [5].

For sound decisions on the case mix, it is important to analyze strategies of hospitals competing for the same market segments. For example, consider a situation where small rural hospitals focus on standardized and frequently occurring procedures to enable sustainable business development. If the case weight of a DRG in a DRG-based reimbursement system is based on average costs for the treatment of patients of this DRG, hospitals with a focus on this DRG might have a competitive advantage due to more efficient process structures. Consequently, patients of this DRG might be of less interest for hospitals that cannot provide the corresponding services efficiently.

Strategy aspects related to time can be of structural importance. It can be of difference whether a hospital sets the tone or follows a defensive strategy reacting to strategic moves of other hospitals. A description of such types of strategies for hospitals is provided by Helmig et al. [10].

In addition to supporting hospital management, modeling case mix strategies in a multi-hospital environment can also be relevant for hospital planners setting up region-wide hospital plans. For example, the availability of supply in rural areas or for unattractive DRGs caused by high variabilities in either demand or resource requirements can be analyzed using such an approach.

Design of case-based reimbursement systems

The design of reimbursement systems and the analysis of associated incentives can be considered as a main contribution of management scientists in the provision of health services [6]. The current practice in Germany for reimbursing patients of a certain DRG is based on average costs [19]. Average costs of a certain year determine the cost weights in the year after next. This practice leads to unintended drawbacks. One major drawback is that patient groups involving high risks can be unattractive for hospitals since hedging risks involves certain costs. Patient-related risks involve uncertain patient demand and uncertain resource requirements. Uncertain demand necessitates reserve capacity to cope with demand peaks. Uncertain resource requirements impose a substantial challenge for operational planning as opposed to standardized procedures. Due to the subadditivity of variabilities, patients involving high risk may necessitate higher average costs for hedging risks for hospitals with low volumes than for large hospitals. Lüthi et al. [16] propose a compensation of financial risk based on the value at risk (VaR). The effects of such compensation mechanisms can be analyzed using case mix planning approaches.

Reimbursement systems have to be designed carefully in order to eliminate or limit reactive subversions. Bevan and Hood [3] describe the behavior of "reactive gamers" in healthcare settings whose goals are largely the same as those of a central controller but who take advantage of the system if they have incentives and opportunities. The following example illustrates such behavior.

Jürges and Köberlein [12] describe the setting of neonatal care where a high share of costs are fixed. Consider a setting where hospitals are reimbursed based on average costs of a representative sample of hospitals including large and small hospitals. Managers of small neonatal care units have to find ways to cover the resulting funding gap between high fixed costs and few patients contributing to the fixed costs. One possible reaction is to identify possibilities to upcode patients. Boundaries between ethical upcoding behavior and semi-legal or even illegal upcoding can be blurred. An example for ethical behavior is to improve coding procedures to omit false downcoding. Systematically swapping primary and secondary diagnosis with the goal of increasing revenue can be categorized as questionable behavior. The managers of the neonatal care unit might have the same principles of providing adequate care of high quality for patients in mind as the designers of the reimbursement system. However, they consider themselves to be forced into actions counteracting the vision of the system designers.

Summarizing, the design of case-based reimbursement systems is highly complex. The unique role of the healthcare industry can necessitate a defensive design of reimbursement systems even if all stakeholders pursue the same major goals.

4 Conclusion

This dissertation on case mix planning consists of three major parts. In the first part, the case mix planning problem is introduced and the research discussed in this dissertation is motivated. The main part consists of four essays on case mix planning. The essays are summarized and the full version is attached in the appendix. The contributions are critically discussed and set in a broader context in the third part. In addition, different areas of improvement potential related to the German hospital reimbursement system are listed and possible areas for future research are sketched.

The main contributions of this dissertation are the following. First, the first literature focusing on case mix planning is presented. Second, a population-based method for forecasting regional hospital demand is presented. Third, a way to consider non-linear resource consumption when planning the case mix is introduced. Fourth, a framework for case mix planning in hospitals is presented generalizing modeling approaches discussed in the literature.

The aim of the presented essays is to provide a deeper understanding of the process of case mix planning. Research topics related to case mix planning span from the transformation of production planning models to the context of hospitals to hospital specific planning issues. Despite its importance, literature on case mix planning is still scarce. However, it recently attracted increasing attention of the research community. Three modeling aspects are addressed in this research to improve case mix planning approaches discussed in the literature. The first contribution combines existing forecasting approaches to define a standardized way to estimate future patient demand. One major advantage of this approach is the use of data that is regularly reported by authorities. The realistic estimation of patient demand is crucial for case mix planning approaches since case mix planning problems are in general highly sensitive to patient demand. This is also true for the second discussed modeling aspect of non-linear case mix planning approaches taking changes in efficiency of resource consumption with increasing scale into account. From a practical perspective, such approaches are particularly relevant when major changes in the case mix are considered. Such changes occur when hospitals are to be restructured or consolidated. From a theoretical perspective, such an approach provides insights to the optimal size and scope of hospitals. Solution methods derived for the solution of non-linear planning can be evaluated and applied to optimization problems in different contexts. The third aspect concerns the value of model extensions to the basic case mix planning problem. Since case mix strategies can have a major impact on all downstream resource planning problems and consequently on hospital performance, they should be evaluated with caution before being applied in practice. A framework is presented to study the effect of case mix strategies on hospital performance.

Concluding, economic pressure due to demographic changes and developments in medicine forces hospitals to further develop strategies to make profit or to break even. Thus, case mix planning can be expected to gain increasing importance in future.

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A Appendix

A.1 Case mix planning in hospitals: a review and future agenda

Hof, S., Fügener, A., Schoenfelder, J., Brunner, J. O., 2017. Case mix planning in hospitals: a review and future agenda. Health Care Management Science 20, 207-220.

The final authenticated version is available online at:
https://doi.org/10.1007/s10729-015-9342-2

Status: published in Health Care Management Science.

A.2 Long-term forecasting of regional demand for hospital services

McRae, S., 2018. Long-term forecasting of regional demand for hospital services.

The printed version is a pre-print of an article submitted to Operations Research for Healthcare.

Status: submitted to Operations Research for Healthcare. Date of submission: June 4, 2020.

Long-term forecasting of regional demand for hospital services

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June 29, 2018

Long-term forecasting of regional demand for hospital services

Abstract

Many western countries undergo substantial demographic changes at present. This is particularly challenging for the health care industry since resources have to be set up and arranged well in advance to be able to cover future patient demand. The objective of this article is to present a method for forecasting regional demand for hospital services. The problem of forecasting regional patient volumes is addressed using a three step approach. First, the population in the region under consideration is projected. Second, future incidence rates are forecasted to account for sociological and medical trends. Forecasting methods in this step include autoregressive integrated moving average models and regression models. Third, patient volumes are anticipated merging the projections of the population and incidence rates for the respective age and sex groups. The proposed method is applied to publicly available data concerning discharges from German hospitals over 16 years. Results indicate that considering the age structure of the population in the catchment area of the hospital and incorporating trends of significantly changing incidence rates is crucial for accurate forecasts.

Keywords: health care, strategic planning, patient demand, forecast

1. Introduction

The share of the population aged over 65 years is expected to nearly double to a share of almost 30% in 2050 on average across OECD countries. This trend is driven by a steady increase in life expectancy at birth of more than three months each year and declining fertility rates (OECD, 2015). The impact of an aging population on health care systems depends on the health status of elderly people even though it is likely that there will be an increasing demand for health services for this age group. Due to this demographic change, long-term projections of the future demand for hospital services are vital for strategic hospital capacity planning since a high share of costs in hospitals is related to long-term investments. Substantial differences in the age structure between different regions need to be adequately addressed to obtain reliable demand forecasts.

The main contribution of this paper is to provide the first case study of long-term forecasts for the regional demand for different hospital services under the consideration of demographic changes. We develop a forecasting approach consisting of three steps. In the first step, the regional population is forecasted considering projections of future birth, death, and migration rates. The second step consists of estimating and projecting incidence rates based on data of a sufficiently large reference population using regression and autoregressive integrated moving average (ARIMA) models. Different types of forecast are used for different patient categories to account for qualitatively different trends in disease rates. The results of these two forecasts are combined in the third step to estimate future regional demand for hospital services. The proposed three step approach is applied to real data from German hospitals. With our approach, we are able to isolate changes in future patient volumes due to changes in demography from other factors such as socio-economic influences and medical developments.

The remainder of this paper is structured as follows. Related literature is discussed in Section 2. In Section 3, methods for forecasting the regional demand for hospital services are presented. In Section 4, these methods are applied to Germany-wide discharge and regional population data for forecasting regional patient volumes of different patient groups. After results are discussed in Section 5, a conclusion is drawn in Section 6.

2. Literature

Increases in the use of hospital services due to an aging population strongly depend on the future morbidity of elderly people (Metz, 1999). There are two opposing main scenarios concerning the development of morbidity in a population with increasing life expectancy. The paradigm of morbidity compression states that the increase in healthy life years is larger than the increase in life expectancy since chronic diseases are compressed at a shorter time span at the end of life (Fries, 1980). In an utopic scenario people would discover full health until a sudden death at the end of the life span. Gruenberg (1977) complains that medical developments focus to a large extent on keeping people alive through medication instead of additionally improving the quality of life resulting in an expansion of unhealthy life years. Christensen et al. (2009) review studies on population aging and health trends. They find that a majority of studies report increases in chronic diseases even though impairments are postponed suggesting at least a relative compression of morbidity. Potential reasons are medical improvements and changes in living conditions. Since 2004, the European Union annually gathers data for the indicator "healty life years" in the European Union Survey of Income and Living Conditions. This indicator is based on mortality information and self-perceived health. In accordance with this data, Rechel et al. (2013) argue that there is compression of morbidity, even though the frequencies of certain diseases increase. Their findings suggest that the challenges of an aging society will be no threat for well organized welfare systems. Olshansky et al. (2005) alert that unfavorable trends such as increases in obesity potentially can even lead to decreases in life expectancy. Parker and Thorslund (2007) note that there is a need to distinguish between different aspects of health since indicators for healthy life years are improving while the number of patients with certain diseases such as chronic diseases or functional impairments increase. Besides these general discussions on morbidity and mortality there exist various studies on trends and the future development of specific diseases. For example, Buttmann-Schweiger et al. (2015) use population-based cancer registries to identify a doubling of age-standardized incidence rates of vulvar cancer. Heidenreich et al. (2011) assume constant prevalence rates of cardiovascular disease and project future costs associated with this disease for the next 20 years in the United States by multiplying average costs with prevalence rates and the corresponding census projection for different age, sex, and ethnicity cells. Shi et al. (2011) use a simulation-based approach to forecast type 2 diabetes prevalence for the next decade. These studies suggest that there is a need to distinguish between different kinds of health services to appropriately meet future demand since incidence rates of certain diseases develop differently.

Forecasts provide a basis for strategic planning in health care (Hulshof et al., 2012). Soyiri and Reidpath (2013) provide an overview on health related forecasting. They stress the fact that health forecasts provide the most value when there is sufficient time to react. Most studies discussing forecasts of the demand for hospital services focus on emergency departments. Wargon et al. (2009) provide a review on emergency forecasts. Frequently discussed topics in this stream of literature are seasonal and cyclic patterns as well as influences such as holidays, events, or weather conditions. Mielczarek (2014) evaluate the impact of demographic changes on emergency services on a regional level via simulation. Moore et al. (2008) discuss time series forecasting of surgical demand. They are able to explain 80% of the variability of the raw data using frequency domain techniques. Dexter et al. (1999) find that using average volumes of the most recent year is an adequate predictor for future use of operating room time and can thus be used for the annual allocation of operating room time to surgical groups. Côté and Smith (2017) present an application of forecasting the demand for the delivery of radiology services. They point out that it can be of interest for health care managers to have access to easily understandable forecasting methods that can be used repeatedly. Goldstein and Gigerenzer (2009) show that simple forecasting rules ignoring major fractions of information can outperform complex forecasting methods since they can turn out to be more robust. Another advantage of simple models is that they are more transparent. Schofield and Earnest (2006) forecast the hospital bed usage for the next 45 years in Australia. They calculate current per capita bed usage for each age and sex group to project future demand. In addition, they use 10 years of historical data to project future trends in bed use per capita for people under and people over 65 years. They use power functions to model trends arguing that they provide the best fit. They analyze the sensitivity of the forecast to different population projections and compare forecasts with regard to whether or not a trend is included. Strunk et al. (2006) forecast future demand for hospital inpatient demand in the United States for a time horizon of ten years. They calculate the current diagnosis related group disease rates for each age, weigh it with the corresponding case weight, and multiply it with the corresponding census projection. While demand for services related to circulatory diseases is expected to increase, diseases related to maternity care will decrease. They find that the development of medical technologies can significantly influence the impact of an aging society on increases in healthcare use. Further, they emphasize that there can be significant differences between different regions. Rais and Viana (2011) provide references to several tutorial-type articles describe different approaches to hospital demand forecasting in their survey on operations research in health care. For example, Beech (2001) describe a forecast of inpatient demand aggregated according to service areas medical/surgical, obstetrics/gynecology, pediatrics, and psychiatry. They project regional demand for these service areas using current rates and the projected population size. They compare this projection to a scenario with declining utilization rates. Myers and Green (2004) list certain examples where medical advances induced changes in inpatient demand in the past.

Summarizing, there are various studies on the development of different diseases or disease categories. Recent research suggests that there are qualitative differences in the development of disease rates of different diseases especially in older age groups. This indicates that demand forecasts accounting for these qualitatively different trends might be promising. There is a large body of literature concerning forecasts of the demand for emergency services. However, literature on long-term hospital demand forecasting is in general sparse. We did not find any studies concerning the forecast of demand for individual hospitals. With this research, we aim to contribute to close this gap.

3. Methods

The demand for hospital services in a specific region is forecasted using a three step approach. The first step consists of a forecast of the population in the region under consideration, in the second step future incidence rates are estimated, and in the third step hospital demand is projected multiplying the forecasted population with the supposed incidence rates.

3.1. Population forecast

Population forecasts are widely available from the level of regional districts to worldwide regions. Thus, a forecast of the population broken down into age and sex groups for the region and time horizon under consideration is often available. Nevertheless, the technique of forecasting populations is sketched to sensitize for possible forecasting inaccuracies.

The size of a population is driven by its fertility rate, mortality rate, and migration (Booth, 2006). The population at period $t+1$ is given by the following formula.

$$P_{t+1} = P_t + B_t - D_t + I_t - O_t \tag{1}$$

The parameter P_t describes the population at period t. The change in population is determined by the number of births B_t, the number of deaths D_t, the number of in-migrations I_t and the number of out-migrations O_t between period t and $t+1$. Typically, cohorts based on age and sex are used for forecasting due to different assumptions of fertility, mortality, and migration between these groups. The development of each of these three factors has to be analyzed to obtain precise forecasts. In addition, scenarios covering a range of possible trends can be used if there is a high degree of uncertainty (Booth, 2006).

In general, the fertility rate in developed countries is primarily driven by lifestyle habits due to advanced medical technologies preventing infant death. Migration can influence fertility rates as well due to different fertility rates in different populations. The majority of the workload of hospitals is generated by older people as will be seen in the following analysis. Thus, the influence of fertility rates on hospital patient volumes is mainly restricted to infant or maternal diseases in a forecasting horizon of up to approximately 50 years. The impact on the majority of other patient groups reveals itself only in the very long run. The mortality rate can change with a variety of factors, such as social, medical, and ecological determinants. The mortality rate has a large impact on hospital volume due to the high frequency of multimorbidities of elderly patients. The increase in life expectancy in developed countries is primarily driven by enhanced treatment methods, especially for cardio-vascular diseases (Tickle, 2016). In general, migration is very difficult to estimate (Hyndman and Booth, 2008). Thus, it is a common approach to analyze different scenarios.

In summary, population forecasts are accurate if mortality and fertility rates underly a stable trend and if there is few unexpected migration. For the task of forecasting hospital demand, it is important to project the future development of mortality rates precisely due to the high share of workload in hospitals caused by elderly patients.

3.2. Projection of incidence rates

In a sufficiently large sample, temporal changes of incidence rates are not prone to high variability in the short run if no epidemics or major environmental influences such as wars occur. Over longer periods of time, however, incidence rates can change significantly. Such changes occur due to alterations in medical treatments as well as social and environmental factors. Note that the term incidence rate is used in the remainder of this article interchangeably with relative frequencies of hospital discharges assuming that differences between those two figures can be neglected. Incidence rates of specific diseases can be influenced actively, e.g., by future research, technical developments, and government decisions. Thus, detailed long-term forecasts relying on past values without anticipating future developments can be biased. As mentioned in the introduction, there is a vivid scientific discourse on the future of incidence rates of elderly people. The actual development of these rates has a high impact on the workload in the health care sector.

The task at hand is to forecast various time series of incidence rates. The forecasting setting is described as follows. Forecasts are evaluated out-of-sample, i.e., each time series is split into a fit period $1, ..., T$ and a test period $T + 1, ..., T + N$. Period T is referred to as the forecasting origin. Based on observations $y_1, y_2, ..., y_T$ future values y_t with $T + 1 \leq t \leq T + N$ are predicted. The parameter N is known as forecast horizon or lead time. Let f_t denote the forecast of y_t. The forecast error e_t is then defined as $\epsilon_t = y_t - f_t$. The quality of the forecasts is evaluated using rolling forecasting origins where the forecasting origin is successively updated. This enables a differentiated analysis of the goodness of the forecast in different phases of the forecasting horizon. Detailed arguments supporting this design are provided in Tashman (2000). If available, additional variables can be considered to be added to improve the forecasts. Conversely, keeping the number of explanatory variables at a low level helps to avoid problems of overfitting.

Regression and autoregressive integrated moving average (ARIMA) models are used for forecasting since these models allow for a trend. Nonseasonal ARIMA models are classified according to the number of autoregressive terms p, the number of nonseasonal differences d, the number of moving-average terms q, and whether a constant term is included. This results in the notation ARIMA(p,d,q) with or without constant. For example, an ARIMA(1,0,0) model with constant is equal to a regression on the previous observed value, an ARIMA(0,1,0) model with constant is a random walk with drift and a ARIMA(0,0,1) model with constant is the same as a regression on the previous forecasting error. The naïve method where all forecasts are simply set to the value of the last observation serves as a benchmark for the considered methods.

The forecasts are evaluated applying different measures on forecast accuracy. The scale dependent measures mean absolute error (MAE) and mean square error (MSE) are used to compare different methods on the same time series. The scale independent methods mean absolute percentage error (MAPE) and the mean absolute scaled error (MASE) are used to compare forecasts of different time series. The four measures used in

Table 1: Definitions of applied measures

Method	Definition
MSE	$\text{mean}\,(\epsilon_t^2)$
MAE	$\text{mean}\,(\lvert\epsilon_t\rvert)$
MAPE	$\text{mean}\left(\left\lvert\frac{\epsilon_t}{y_t}\right\rvert\right)$
MASE	$\text{mean}\left(\left\lvert\frac{\epsilon_t}{\frac{1}{n-1}\sum_{i=2}^{n}\lvert y_i - y_{i-1}\rvert}\right\rvert\right)$

the analysis are defined in Table 1. They are motivated and discussed in Hyndman and Koehler (2006).

3.3. Calculation of future demand

Future inpatient volumes are forecasted multiplying projected relative frequencies of diseases of a reference population in the respective year with the forecasted size of the population in the region under consideration for each age and sex group. Thereby it is assumed that the influence of regional components other than the distribution of the characteristics age and sex such as environmental factors or the level of urbanization can be neglected.

4. Results

The presented methods to forecast the demand for hospital services are applied to the city of Augsburg, a German city with a population of about 0.3 million people. There is one maximum care provider with 1,741 beds and 8 smaller, partially specialized hospitals with a size between 100 and 400 beds, resulting in a total of 3,314 beds. The German population is chosen as reference population facilitating the projection of age and sex specific birth, disease, and death rates. The underlying assumption is that lifestyle habits and other factors influencing these factors are roughly the same in the area under consideration and Germany.

4.1. Population forecast

In Germany, there is a slight shift of fertility rates towards older ages as can be seen in Figure 1. Similarly, there is a steady shift in death rates to older age groups (Figure 2) with a corresponding increase in life expectancy at birth from 70.6 years in 1970 to 80.9 years in 2012.

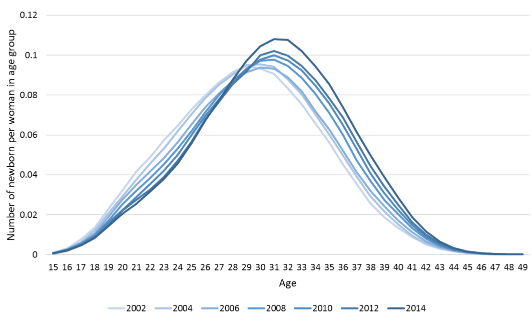

Figure 1: Developments in fertility in the last decade

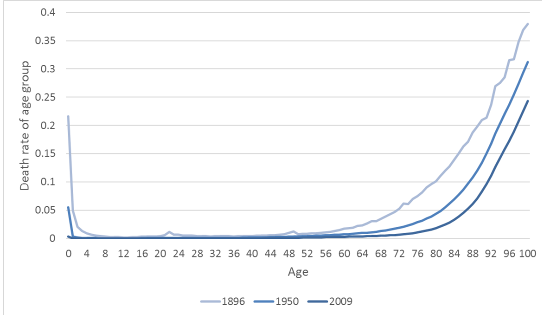

Figure 2: Developments in mortality in the last century

Population forecasts until 2030 for Augsburg are provided by the local government. Figure 3 shows the population pyramid of the current population and a projection of the year 2030. The forecasted population pyramid has the shape of an urn due to a currently low number of women in the childbearing age groups and increases in life expectancy.

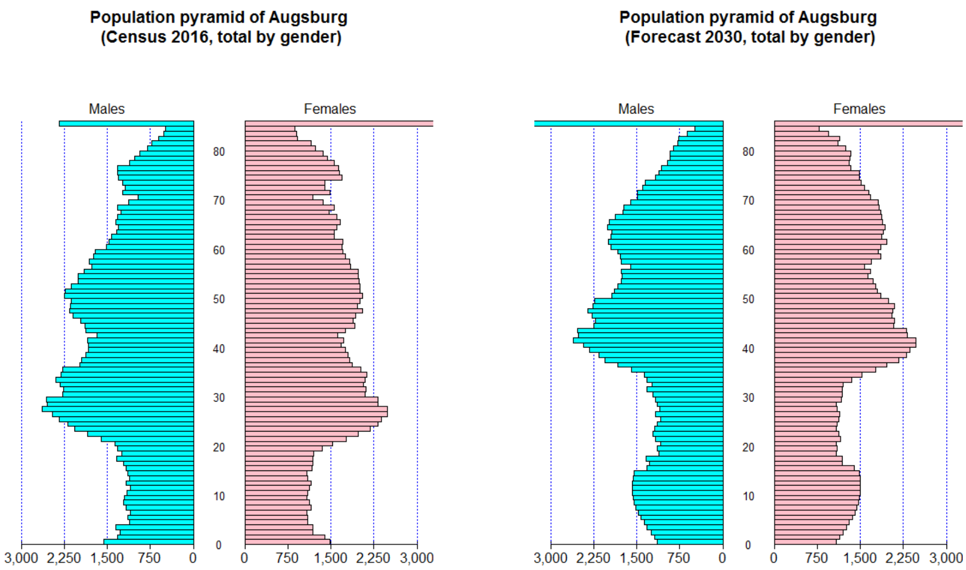

Figure 3: Demographic change in Augsburg

4.2. Projection of incidence rates

Different diseases and disorders require different resources for diagnosis and treatment. Incidence rates are projected using the International Statistical Classification of Diseases and Related Health Problems (ICD). Data on four character ICD codes broken down by age group and sex are provided for each year since 2000 by the German Federal Statistical Office (e.g., Statistisches Bundesamt 2017). The data contains all inpatients of German hospitals discharged in the respective year. The ICD codes are grouped and aggregated by the first character. These groups will be denoted in the remainder as ICD-1 categories. This level is comparable to the level of Major Diagnostic Categories. The incidence rates of each of the 22 ICD-1 categories are forecasted individually for each age group and sex. Incidence rates are calculated by dividing the number of patients in each group by the corresponding population. The population itemized by age and sex is also provided annually by the German Federal Statistical Office (e.g., Statistisches Bundesamt 2016). The respective reference date is the last day of the year.

4.2.1. Status quo and previous development

Currently, the relative frequency of hospital inpatient discharges in Germany is in average below one hospital stay each five years until the age of 54. Figure 4 illustrates the relative frequency of hospital inpatient discharges broken down by age groups. The frequency is notably higher in older age groups. The local peak between 30 and 34 can be explained by maternal diseases.

Different diseases dominate in different age groups and sexes. This is illustrated for the 5 ICD-1 categories with the highest volume and the ICD-1 category O representing diseases related to maternity in Figure 5. First, there are notably differences between different ICD-1 categories. Most incidence rates of ICD-1 categories increase with increasing age. However, there are notably differences. For example, for diseases of the musculoskeletal system and connective tissue (M) and neoplasms (C), the incidence rate, or more precise, the relative frequency of hospital discharges, shrinks in very high age groups. This indicates that for elderly people the risks of critical interventions can outweigh the benefits. Second, women and men are prone to different diseases despite there are similarities for different ICD-1 categories. Most obviously, maternal diseases are only present in the female fertile age groups.

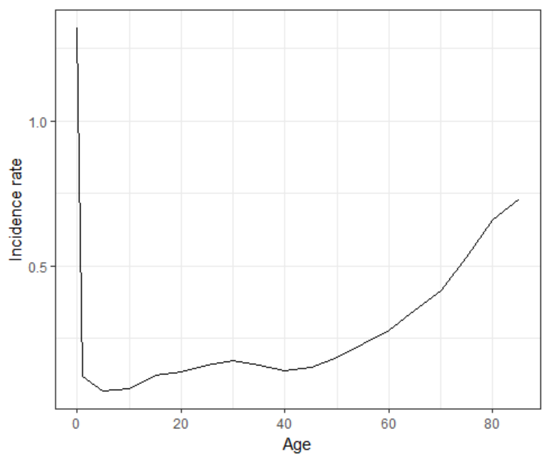

Figure 4: Incidence rate of hospital inpatient discharges by age group 2016

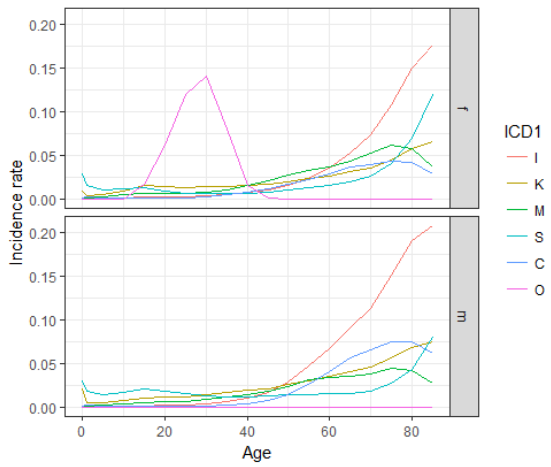

Figure 5: Incidence rate by age group and sex of selected ICD-1 categories 2016

Different patient groups show different developments as can be seen in Figure 6. From 2000 to 2016, there is a slight shift of incidence rates to older age groups in the ICD-1 categories diseases of the circulatory system (I), diseases of the musculoskeletal system and connective tissue (M), and neoplasms (C). In contrary to the sole shift in category I, there is a increase of incidence rates in category M and a decrease in category C

Table 2: Rolling forecasting origins

	Training					Test				
Forecasting origin T	2000	2001	2002	2003	2004	2005	2006	...	2015	2016
2004	y_1	y_2	y_3	y_4	y_5	f_6	f_7	...	f_{16}	f_{17}
2005	y_1	y_2	y_3	y_4	y_5	y_6	f_7	...	f_{16}	f_{17}
...										
2015	y_1	y_2	y_3	y_4	y_5	y_6	y_7	...	y_{16}	f_{17}

especially in older age groups. Rates of injuries (S) increase for older age groups while rates of diseases of the digestive system (K) do not change substantially.

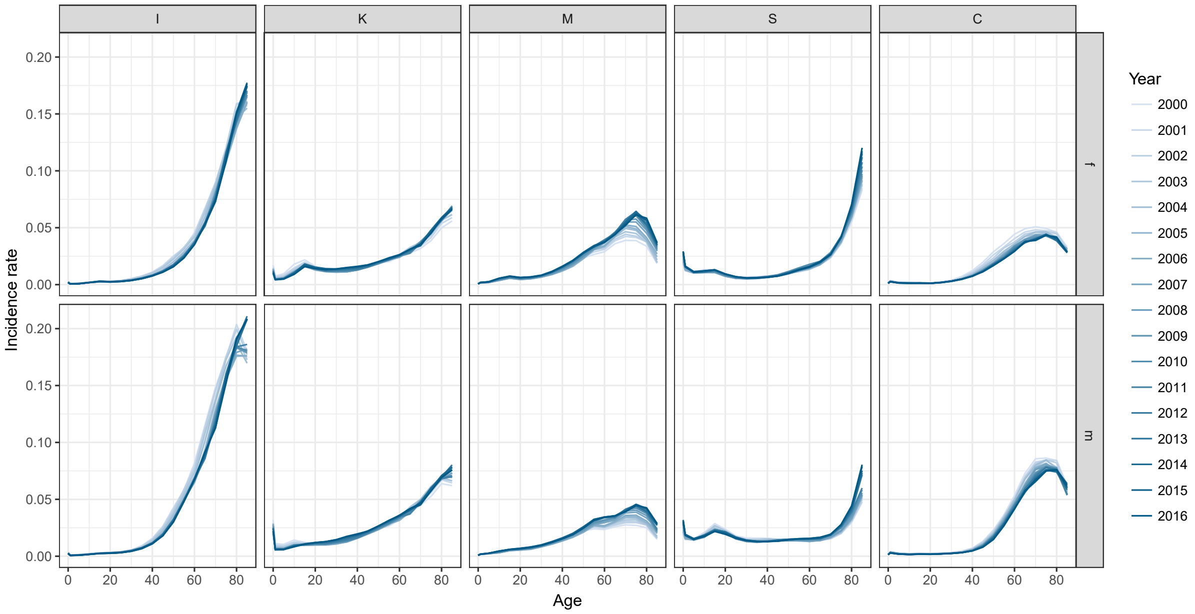

Figure 6: Development of relative frequencies of ICD-1 categories

4.2.2. Forecast

The data is split into a training and a test set for each iteration of the rolling forecasting origin approach. The training set is increased from 5 periods at the start to all but one period at the end of the method. The test set consists of the remaining periods. Table 2 illustrates the different training and test sets for each forecasting origin T from 2004 to 2015. The statistical software R is used for all forecasts.

Qualitatively diverse developments between ICD-1 categories and age groups indicate the effectiveness of using different forecasting methods for certain combinations of ICD-1, age, and sex groups. For each of the 22 ICD-1, 19 age, 2 sex groups, and 12 forecasting origins, forecasts obtained by the naïve method, regression, and the ARIMA model without seasonality that provided the best fit to the training data are evaluated.

The forecasts providing the best fits in each age group are illustrated in Figure 7 for males in ICD-1 C and the forecasting origin 2008. For each age group, the forecasting method with the lowest MAE is used to forecast incidence rates. This implies that for different age groups different forecasting methods are potentially used. For this forecast with forecasting origin 2008, incidence rates from the years 2000 to 2008 are used to forecast incidence rates from 2009 to 2016. The forecasted incidence rates can be visually compared to the actual values of the incidence rates between 2000 and 2016 depicted in Figure 8. The value of allowing for a trend in the forecasting model reveals in the higher age groups where a stationary forecast would perform considerably worse as can be seen when analyzing the observed values in Figure 8 which are clearly non-stationary.

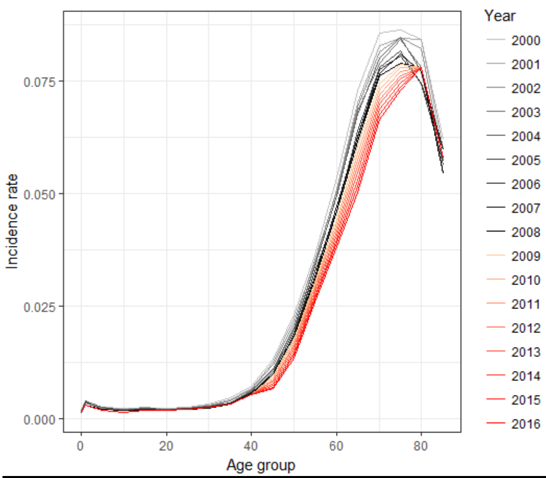

Figure 7: Forecasted values ICD-1 C, male, forecasting origin 2008

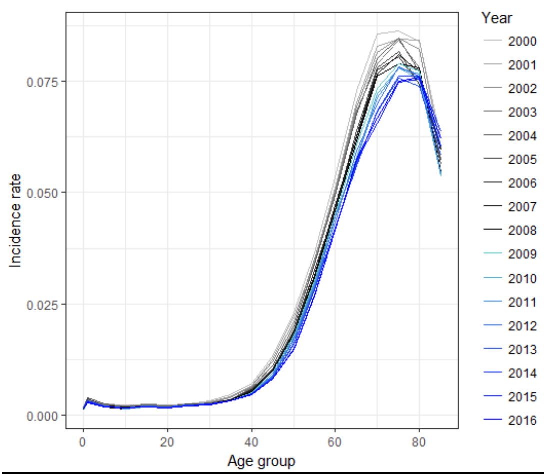

Figure 8: Observed values ICD-1 C, male

Table 3 gives an overview over the number of times each of the models performed better than the other models. The fact that the naïve method outperforms other methods in two out of three forecasts can be explained by the high proportion of stationary time series especially in age groups with low incidence rates. The remaining forecasts are equally divided between simple regression and the ARIMA model that provided the best fit. The best performing ARIMA models dominating the naïve method and regression include non-stationary and stationary models. The most suitable non-stationary models are ARIMA(0,1,0) with constant which is a random walk with drift and ARIMA(0,2,0) where the most recent value and the most recent change is used for forecasting the next period. The stationary method ARIMA(0,0,0) with constant is a white noise model shifted by the constant.

One of the main advantages of the rolling forecasting origin approach is the possibility of comparing the quality of the forecast for different forecasting horizons. As expected, the forecasts are more precise for short-term forecasts as can be seen in Figure 9. This figure illustrates the performance of the proposed forecasting procedure as measured by the MAE averaged over the different age, disease, and sex groups for different forecasting origins. The forecasting origin is depicted on the x-axis. When using the year 2004 as forecasting origin, i.e., using the data from 2000 to 2004 to forecast the years from 2005 until 2016, the average MAE is marginally higher than $1.25 \cdot 10^{-3}$. In general, the quality of the forecasts increases as the forecasting origin increases. For example, the average

Table 3: Dominating forecasts

Model	Number of outperforming forecasts
Naïve method	6652
Regression	1748
Best fit ARIMA	1632
- ARIMA(0,1,0) w. constant	518
- ARIMA(0,0,0) w. constant	484
- ARIMA(0,2,0)	256
- Other ARIMA models	374
Total number of forecasts	$22 \cdot 19 \cdot 2 \cdot 12 = 10032$

MAE when considering 2009 as forecasting origin, i.e., forecasting the incidence rates from 2010 to 2016 with data from 2000 to 2009, is approximately $7.5 \cdot 10^{-4}$.

The outlier in 2011 can be explained by the census in 2011 in Germany since the current population is calculated updating the population at the respectively last census solely relying on officially registered birth, death, and migration counts. An artificially high decrease of the population by 1.4 million people from 2010 to 2011 results in falsified increases of disease rates leading to inferior forecasting results when using 2011 as forecasting origin.

Figure 10 illustrates which models provide the best fit for each forecasting origin. The y-axis describes the relative frequency of a model outperforming the other models. For example, a value of 0.2 for the regression (LM) for $T = 2007$ implies that in 20% of all ICD-1, age, and sex groups the regression outperformed the other models when considering forecasts from 2008 to 2016 based on data from 2000 to 2007. When comparing the best performing methods in the course of the rolling forecasting origin approach, the major trend is that regression performs better in a higher proportion of forecasts for long time ahead forecasts and the naïve method is more powerful for short-term to medium-term forecasts than for forecasts with very long lead times.

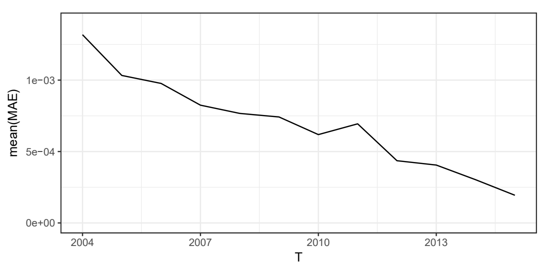

Figure 9: Performance of forecasting models with increasing forecasting origin T

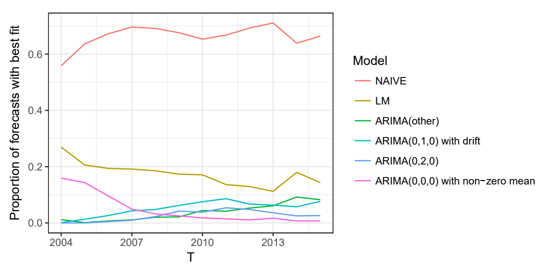

Figure 10: Best models with increasing forecasting origin T

In the following, the forecast providing the best fit according to the training data as measured by the MAE for each ICD-1, age, and sex group and each forecasting origin is referred to as the *best fit forecast*. The best fit forecasts are compared with forecasts restricted to one of the three methods naïve, regression, and ARIMA in Table 4 using

Table 4: Comparison of different forecasting methods

Model	Mean of MAE	Mean of MAE (group size $\geq 10,000$)
Best fit forecast	0.00069	0.0012
Only naïve method	0.00091	0.0016
Only regression	0.0028	0.0051
Only best fit ARIMA	0.0013	0.0023

the mean of the MAE over the forecasts for each combination of ICD-1, age, and sex group and each forecasting origin. The best fit forecast performs about 25% better than forecasts derived only by the naïve method. Regression and ARIMA models perform considerably worse if considered as stand-alone forecasting methods. Since the quality of forecasts for combinations of age, sex, and ICD-1 groups with sparse patient counts are not relevant, the results are further analyzed considering combinations with more than $10,000$ patients in 2016. These combinations account for about half of the forecasts and more than 90% of all patients. Qualitatively, the results are similar. Regression and best fit ARIMA perform relatively better when considering only the relevant combinations suggesting that they are useful methods for forecasting the relevant patient groups.

4.3. Calculation of future demand

Finally, future demand for the ICD-1 categories is estimated for the years from 2017 to 2030 multiplying the projected population for each age and sex group with the respective forecasted incidence rates. The incidence rates are forecasted using the best fit forecast as described in the previous section. The results are aggregated by ICD-1 category to obtain the forecasted future patient volumes in the region under consideration for each ICD-1 category. The absolute forecasted volumes are compared with the current values and a naïve forecast in Figure 11. For the naïve forecast it is assumed that the incidence rates in 2030 are similar to those in 2016. Thus, the change in volumes between 2016 and 2030 is assumed to only depend on the age structure for the naïve forecast. Differences between the best fit forecast and the naïve forecast are rather small for most age ICD-1 groups with the exception of ICD-1 category I while there exist larger differences between the current and the forecasted volumes. This indicates that the age structure should be taken into account when forecasting patient volumes in a population with substantial demographic changes. The most striking increases are expected for diseases of the musculoskeletal system and connective tissue (M), symptoms, signs and abnormal clinical and laboratory findings (R), and infectious diseases (A) as can be seen in Figure 12. The volumes of the ICD-1 categories O and Z related to deliveries are expected to decrease due to a lower number of women in the childbearing age groups.

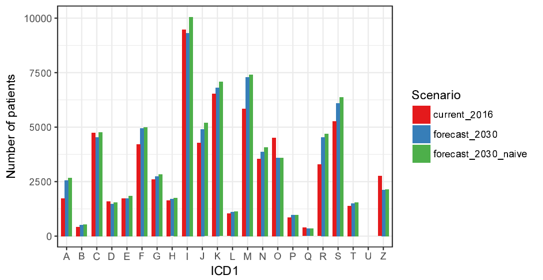

Figure 11: Final forecast of patient volumes for the city of Augsburg

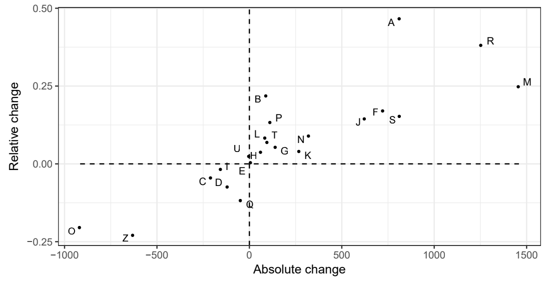

Figure 12: Absolute and relative change of ICD-1 categories

5. Discussion

The aim of the proposed method is to forecast future patient volumes for a region. Inputs include previous population distributions and previous patient volumes for the region under consideration. Patient volumes of a reference population can be used as a substitute if disease rates can be expected to be similar for the respective age and sex groups. The latter approach is used in the previous section. The quality of the patient count of the German Federal Statistical Office can be expected to be very good since the ICD counts are relevant for hospital billing. Consequently the nationwide relative frequencies are reliable. The advantage of using frequencies of a large reference population is that they are more robust in comparison with results of very small populations. However, regional patient counts should be considered if they are available since regional particularities such as environmental conditions might lead to different frequencies. The level of ICD-1 categories is chosen in the analysis to avoid drawbacks of very detailed forecasts such as large statistical uncertainties which worsen the quality of the forecasts considerably. However, a more detailed level should be preferred if one is interested in projections of more detailed patient categories. It has to be noted that incidence rates and relative discharge rates can deviate depending on factors such as supply and treatment recommendations. Since discharge rates are used as training data for the forecast and the relevant result of the forecasts are patient volumes, these differences can be neglected. Population forecasts can be assumed to be decent since they are used for a variety of different tasks. However, new census data can lead to serious corrections as it was the case for the census in 2011 in Germany.

A more severe problem for forecasting patient volumes based on ICD groups are adjustments between the different updates of the ICD catalog. The latter is important since due to changes in case-based reimbursement systems incentives might occur to use different treatments or classifications for patients. In addition, new technological treatment possibilities and the adaptation of treatment recommendations can be reasons influencing patient volumes significantly. Since such developments are difficult to foresee, it is reasonable to consider them as random influences.

Obviously, the forecasting setting has to be adapted to the amount of available data.

Models with few parameters should be preferred if only short reliable time series exist to avoid the risk of overfitting. The complete three step approach should be validated using regional patient counts if this data is available. In general, this data is hard to estimate if catchment areas of hospitals overlap to a large extent since information on the residences of hospital patients is not publicly available.

6. Conclusion

In this paper, a three step approach for forecasting regional patient demand in the long run is presented. The method combines population forecasts with forecasts of incidence rates to obtain estimates of future patient volumes. Methods for forecasting incidence rates include regression and ARIMA models. Those models are embedded in a rolling forecasting origin approach to assess the quality of forecasts with respect to different forecasting horizons. The model that provides the best fit to the respective training set is used for forecasting future incidence rates.

The forecasting approach is applied using aggregated discharge data of all German hospitals over 16 years to forecast patient volumes for the city of Augsburg in Germany. Forecasting assumptions of this case study include that there are no major differences with respect to incidence rates between age and sex groups of the regional and the German population.

Results emphasize the need of taking the distribution of the patient population into account for forecasting future patient volumes especially if substantial demographic changes can be expected. The consideration of the development of incidence rates is important for such groups where major trends exist. In the short run, the naïve forecast where the last known value is used to forecast the demand turns out to be effective. The importance of considering forecasting models allowing for a trend increases with increasing forecasting horizon. For some patient groups, it is important to include stationary models in the testing phase of long-time forecasts as well to avoid the risk of overfitting.

Summarizing, a simple tool using freely available data is presented to forecast regional patient demand in the long run. The method can be extended in further research to estimate future resource needs by mapping diagnosis related data to resource related data such as average resource requirements for different Diagnosis Related Groups.

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A.3 Analyzing economies of scale and scope in hospitals by use of case mix planning

McRae, S., Brunner, J. O., Bard, J. F., 2020. Analyzing economies of scale and scope in hospitals by use of case mix planning. Health Care Management Science 23, 80-101.

The final authenticated version is available online at:
https://doi.org/10.1007/s10729-019-09476-2

Status: published in Health Care Management Science.

A.4 Assessing the impact of uncertainty and the level of aggregation in case mix planning

McRae, S., Brunner, J. O., 2020. Assessing the impact of uncertainty and the level of aggregation in case mix planning. Omega 97, 102086.

The final authenticated version is available online at:
https://doi.org/10.1016/j.omega.2019.07.002

Status: published online in Omega.