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# Comparing the Financial Risk of Bed-Day and DRG Based Pricing Types Using Parametric and Simulation Methods

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**Abstract.** The extent of random financial risk involved in the Finnish bed-day and Diagnosis Related Groups (DRG) based hospital pricing systems were estimated and compared using parametric and simulation methods. DRG based payment schemes were found to provide significantly better protection against financial risk for municipalities, but municipality's size was the main determinant of financial risk. Small municipalities should use longer contracts between hospitals or form bigger purchaser-organisations for risk pooling. In addition, the current risk management system proved to be ineffective in decreasing the random variation in total costs.

## 1. Introduction

The problem of risk sharing exists in insurance based private health care financing systems as well as in tax based public systems. Financial risk prevails because a third-party payer can never predict exactly the number of patients appearing, or their case severity and resource use [1]. However, in the literature, risk sharing is predominantly understood to be the tradeoff between efficiency and patient selection, especially in private and insurance based systems such as in the USA and the Netherlands [2,3]. In pure public health care systems patient selection is not usually considered as a problem between the third-party payer and hospital, because the financing of hospitals is based on taxes and they are not allowed to select patients. Instead, resource allocation discussions between a third-party payer and a producer include sharing of the financial risk arising from need and the randomness of public health services.

This study focused on estimating and describing the extent of the financial risk relative to the population base of the third-party payer in the Finnish public health care system. Most of Finland's municipalities, which are responsible for health care financing, have a very small population base. The financial risk is estimated by comparing the cost distributions of the municipalities using two different hospital pricing systems – bed-day pricing and Diagnostic Related Groups (DRG) based pricing.

In the US Medicare, DRG based pricing has been used since 1983 [4]. DRG based pricing was introduced into the public health care systems of Sweden and Norway, among others, following health care financing reforms at the start of the 1990s [5–8]. Since Finland's hospital financing reform in 1993 hospital pricing has been continually modified, and DRG based pricing is gaining a strong foothold. Finland therefore provides a natural setting for comparing the financial risks of the traditional system (bed-day pricing) with the novel (DRG pricing).

The study also aimed to evaluate the ability of the current Finnish risk management system to smooth out the risk. A major problem faced by the small individual municipalities has been the poor reliability of annual budgeting and the financial risk due to random cost variations in specialised hospital care. The present study suggests a framework for modelling the financial risks of hospital care for each municipality individually. This framework allows the smaller municipalities to relate the risk to total health care budget and to assess the need for risk management.

A simulation technique using parametric assumptions has been used to study the financial risk of GP fundholders in the UK [9,10] and the financial risk to hospitals in the USA [11]. In a previous Finnish study the financial risk of different hospital invoicing systems in Finnish municipalities has also been compared using similar methods to those in the UK studies [12].

This study used and compared two different methods – parametric and non-parametric – to estimate the financial risk of a municipality. Such methods have not earlier been applied to this kind of study.

## 2. Background

### 2.1. Finnish municipal health care system

In Finland the local administrative units, municipalities, are responsible for providing and financing health care services for their residents. The Finnish municipal health care system is hierarchical and organisationally divided into primary and specialised health services. Public specialised care is primarily provided by 20 hospital districts which are administratively federations of municipalities. The hospital districts

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own and run public general and mental hospitals, which are divided into three categories: university, central and other municipal hospitals (regional hospitals). University hospitals are central hospitals for their own districts and provide tertiary level services for surrounding districts.

The median size of municipalities is about 5000 inhabitants, but they range from about 200 citizens to over 500 000 in the capital (Helsinki). Although 403 of the 452 municipalities have units of under 20 000 inhabitants, 58% of the Finnish population live in municipalities (49) with over 20 000 citizens. In terms of the financial risk of hospital care, the Finnish arrangement is exceptional, e.g., the counties in Sweden and Norway are much larger units for pooling the financial risks of hospital care. In the existing Finnish system, only in the most costly cases do the federations of municipalities, i.e., hospital districts, cover an individual patient's costs exceeding a fixed limit of FIM 100 000–300 000 (17 000–51 000 EUR), which varies across districts.

The municipalities finance their obligations from municipal taxes (70%), state subsidies (20%) and user charges (10%). State subsidies, designed to equalise economic disparities between the municipalities, are paid as a lump sum according to a capitation formula based on demographic and socioeconomic factors.

*2.2. Present hospital pricing systems*

Municipalities purchase services for their citizens from hospitals, which invoice municipalities using various pricing structures: bed-day prices, a combination of fee-for-service and bed-day prices, and case-based prices. Consequently, current methods and procedures for defining services and setting prices vary considerably between hospital districts.

Prices are set prospectively by the hospitals or hospital districts and confirmed by the district boards. A case-based price includes all services involved in inpatient care (e.g., X-rays, laboratory tests, surgical procedures and accommodation) required for a 'standard' treatment of a 'normal' inpatient, defined by cause or type of treatment, e.g., hip replacement. In the fee-for-service type of pricing, operations and bed-days are invoiced separately. While case-based prices are being used increasingly by hospitals or hospital districts, they are still usually only applied to certain surgical operations, with other operations or treatments being invoiced using prices per bed-day. By the year 2000 most hospital districts had considered using DRGs for pricing their services. DRG based pricing takes a patient's age, sex and any comorbidity into account, while case-based prices are determined without patient specific information. There are also pricing variations in specialised outpatient care. Charges for specialists' consultations are usually set as a price per visit, and categorised according to the type of treatment.

Municipalities have thus been largely passive purchasers of hospital services in recent years. Being economically responsible for their own hospital district, they seldom purchase services outside it. Unlike in Sweden and the UK no provider–purchaser split of any kind has been introduced. In addition, the heterogeneity of pricing systems means that municipalities are not able to compare hospital services and their prices like-for-like, while small municipalities in particular have no expertise in negotiating volume for hospital care.

*2.3. Potential changes in risk sharing*

In theory, municipalities could transfer a part of the financial risk to hospitals using, e.g., contract controlled budgets and different pricing systems. However, in practice hospital pricing systems are developed by hospital districts, which operate as monopolies in their local area. In the case of budget deficits, extra money can usually be granted at the discretion of the municipal authorities. Although the hospital districts cover the costs of the very expensive cases above a fixed limit, unpredictability in total costs remains a persistent problem in budgeting for many municipalities.

*2.4. Risk consequences of different pricing types*

Financial risk-sharing between a third-party payer and a provider is often understood to consist of a combination of systematic and random risk [13,14]. This study considers only the random component of risk sharing; the incentive effects due to risk sharing and different pricing systems are not dealt with. In Finnish health care the municipalities and hospitals are 'transactors' that come to an agreement about the amount to be paid dependent or independent of the occurrence of uncertain events [15]. Hospital prices represent part of the payment scheme agreed between the transactors. At one extreme, if a municipality sets only a fixed budget at the beginning of the year, hospitals bear the whole random financial risk. On the other hand, if a hospital invoices using bed-day prices or fee-for-services, rolling their all costs into prices (as in most cases in practice), the municipality bears the whole risk.

Previous studies have shown that changing from cost-based reimbursement to fixed prices increased the risk (systematic and unsystematic) for hospitals [16,17]. Similarly, if the payment scheme was based on the nationally determined fixed DRG prices, hospitals would bear more financial risk compared to a bed-day payment scheme (see table 1).

Nevertheless, our hypothesis based on general statistical assumptions and the results of previous studies is that the total random financial risk depends more on the size of the municipal population than on the type of pricing applied [9,10,12].

Table 1
Risk consequences using various types of hospital financing in the Finnish system.

| Financing type | Risk for municipality | Risk for hospital |
|---|---|---|
| Fixed/Global budget | – | Bear all risk |
| Case-based price | Risk sharing | Risk sharing |
| Fee-for-service/ bed-day price | Bear all risk | – |

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## 3. Data

The data obtained from the data warehouse of the Finnish hospital benchmarking project covered all outpatients and inpatients (1 423 648 patients) and their incurred costs. The data warehouse contained all episodes of somatic specialised care (specialised care without psychiatric care) in public hospitals in 1999. The total financial risk of somatic care is described using the cost data on outpatient and inpatient patients.

The psychiatric inpatients were obtained from the Finnish Health Care Register (FHCR). The 1999 psychiatric inpatient data were combined with the somatic because the longer treatment periods of psychiatric care were assumed to have an effect on the extent of the financial risk. Psychiatric outpatient visits were not available. Table 2 contains summary statistics on the number of patients and their costs.

Two separate pricing types – a bed-day price and a DRG based price – were formed from the cost data. In the existing system the bed-day price is the most traditional pricing type and still in common use, whereas DRG based pricing is an innovation in Finnish hospital pricing systems.

The average bed-day prices and average prices per outpatient visit were calculated using the incurred total costs, bed-days and outpatient visits for each speciality and hospital separately.

The unknown and small miscellaneous specialities were combined and labelled as ‘other specialities’.

The total costs $c_1$ for each patient were calculated using the average bed-day prices in each hospital and speciality the patient has visited, and summing the patient’s ward episodes and outpatient visits together:

$$c_1 = \sum_{i=1}^{k}\sum_{j=1}^{n} p_{ij}^{d} d_{ij} + \sum_{i=1}^{k}\sum_{j=1}^{n} p_{ij}^{v} v_{ij},$$

where $k$ is the total number of hospitals, $n$ – the total number of specialities, $p_{ij}^{d}$ – average price per bed-day in hospital $i$ and speciality $j$, $d_{ij}$ – inpatient days in hospital $i$ and speciality $j$, $p_{ij}^{v}$ – average price per visit in hospital $i$ and speciality $j$, and $v_{ij}$ – outpatient visits in hospital $i$ and speciality $j$.

The DRG price per patient was calculated by summing the patients’ DRG weighted discharges multiplied by the average cost of a treatment period (1687 EUR). This procedure was used separately for inpatient care only (613 554 patients). For the estimation of the total financial risk, the total costs per patient $c_2$ were calculated by linking patient’s inpatient admissions and outpatient visits together and multiplying each by their unit prices.

$$c_2 = \sum_{g=1}^{499}\sum_{i=1}^{k} \lambda_g \cdot e_{gi} + \sum_{i=1}^{k}\sum_{j=1}^{n} p_{ij}^{v} v_{ij},$$

where 499 is the number of DRG groups, $k$ – the number of hospitals, $n$ – the number of specialities, $\lambda_g$ – the DRG cost weight in DRG-group $g$, $e_{gi}$ – the number of discharges in DRG-group $g$ and hospital $i$, $p_{ij}^{v}$ – average price per visit in hospital $i$ and speciality $j$, and $v_{ij}$ – outpatient visits in hospital $i$ and speciality $j$.

The average bed-day price in psychiatric inpatient care (one price for all bed-days: 190 EUR) was obtained using the total costs of psychiatry and the total sum of bed-days. Unfortunately, it was not possible to yield DRG prices for psychiatric patients.

Table 2
Data description

| | Somatic inpatient care | Somatic inpatient care + outpatient visits | Somatic + psychiatric inpatient care |
|---|---|---|---|
| Number of patients | 613,554 | 1,423,648 | 703,536 |
| Average DRG price per patient EUR | 2,123 | 1,041 | |
| Standard deviation | 3,251 | 2,379 | |
| Average price per patient EUR (based on bed-day price) | 2,780 | 1,324 | 6,441 |
| Standard deviation | 5,322 | 3,762 | 26,856 |

## 4. Methods

In order to model the total annual costs of care the aggregate costs covering all patients in a municipality were considered to be of the form

$$S = \sum_{i=1}^{N} X_i,$$

where the $X_i$’s represent the individuals’ costs and $N$ represents the total number of persons who have caused some costs. In other words, it was assumed that variation in the aggregate costs is caused by two random processes: the number of patients appearing and their resource use.

A parametric approach is based on distributional assumptions, while the non-parametric is accomplished using bootstrapping as a simulation method. The parametric method was employed to investigate the case of using an average cost distribution (of individuals) for all municipalities in the analyses instead of municipality’s own cost distribution. A non-parametric method was then used to estimate the risk consequences of random cost variation for each of the 452 municipalities separately.

### *4.1. Parametric methods*

For the parametric modelling of $S$, let $N, X_1, X_2, \ldots,$ be independent random variables, where $N$ is a nonnegative integer-valued random variable and $X_1, X_2, \ldots$ are identically distributed, i.e., $X \approx F$. The random variable $S$ is considered as a compound distribution given by

$$G = \sum_{n=0}^{\infty} F^{*(n)} p_n,$$

where $p_n$ is the probability function of $N$ and $F^{*(n)}$ is the $n$-fold convolution of the distribution function $F$.

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If the expectations and variances of $X$ and $N$ are known, the expectation and variance of $S$ can also be derived using the conditional expectation formula:

$$E(S) = E_N\big[E(S|N)\big] = E_N\big[NE(X)\big] = E(N)E(X) \quad \text{and}$$
$$\operatorname{var}(S) = E_N\big[N\operatorname{var}(X)\big] + \operatorname{var}_N\big[NE(X)\big] = E(N)\operatorname{var}(X) + \operatorname{var}(N)\big[E(X)\big]^2.$$

In order to calculate the distribution function of $S$ completely, it is needed to specify the distributional families of $X$ and $N$. Instead of using the complicated exact form of the function $G$, it is possible to approximate the distribution function of $S$ using the technique known as Panjer recursion [18,19]. The idea here is to approximate the distribution of $S$ by the probability mass function $g(i)$. If there exist constants $a$ and $b$ such that the distribution of $N$ satisfies the recursion

$$p_n = \left(a + \frac{b}{n}\right)p_{n-1}, \quad n \in \{1, 2, \ldots\},$$

then it is possible to evaluate $g(i)$, $i \in \{1, 2, \ldots\}$, recursively as

$$g(i) = \sum_{j=1}^{i}\left(a + b\frac{j}{i}\right)f(j)g(i-j)$$

starting with $g(0) = p_0$, where the $f(j)$, $j \in \{1, 2, \ldots\}$, denotes the probability mass function of the discretised distribution of $X$. For example, if $N$ has a binomial distribution, then the recursion relation is satisfied with $p_0 = (1-\theta)^k$, $a = -\theta/(1-\theta)$ and $b = (k+1)\theta/(1-\theta)$.

### *4.2. Non-parametric methods*

The strict parametric assumptions for the distributions of $X$ and $N$ can be relaxed using a non-parametric bootstrapping simulation technique [20]. For the non-parametric modelling of $S$, let the observed costs vector be of the form $z = (z_1, z_2, \ldots, z_N, z_{N+1}, \ldots, z_k)$, where $z_1, \ldots, z_N$ are the costs of $N$ individuals, $z_{N+1}, \ldots, z_k$ are zeros and $k$ ($\geqslant N$) represents the upper limit of the risk population (for example, the total population of municipality). Obviously, the materialised aggregate costs are of the type $s = z_1 + \cdots + z_k$. Now, obtaining bootstrap samples of the form $z^* = (z_1^*, \ldots, z_k^*)$ by randomly sampling $k$ times, with replacement, from the original independent data points $z_1, \ldots, z_k$, we can calculate the bootstrap replicate of aggregate costs $s^* = z_1^* + \cdots + z_k^*$. Using $B$ replications, $B \in \{1, 2, \ldots\}$, the bootstrap estimator for the $100 \cdot \alpha$th percentile of the distribution $S$, $\alpha \in [0, 1]$, is the $B \cdot \alpha$th value in the ordered list of the replications and the mean of $S$ is the mean of bootstrap replications.

Every data point in the bootstrap sample has the probability $\hat{\theta} = N/k$ to be a nonzero observation. Since the observations are assumed to be independent, the number of nonzero observations in the bootstrap sample has a binomial distribution and the amount of nonzero costs is drawn randomly from the empirical cost distribution. In the case of compound binomial distribution, the Panjer recursion and the bootstrap simulation with analogous cost distributions yield, in principle, equivalent results.

### *4.3. Specification of models*

Assuming that every individual in a municipality has an equal probability of becoming a patient, the number of patients is distributed as a binomial random variable with parameters $k$ (size of risk population) and $\theta$ (probability of becoming a patient), i.e., $N \approx B \in (k, \theta)$ with expected value $E(N) = k\theta$ and variance $\operatorname{var}(N) = k\theta(1-\theta)$. The assumption of equal probability holds for the expected total number of patients in a municipality and the resource use is determined from the cost distribution $X$.

In the estimation of financial risk, three types of models were used (models 1–3).

In model 1 the number of individuals having an illness spell was assumed to be binomially distributed, and the patient's cost distribution was assumed to follow a log-normal distribution. The parameters for both distributions were expected to be based on national averages. In model 2 the number of patients was based on the observed number of individuals having an illness spell in the municipality. The distribution of costs was assumed to be similar to model 1. In model 3 the data were used to sample both the cost distribution and the (binomially distributed) expected number of patients for each municipality.

Models 1 and 2 were estimated using the Panjer recursion technique. In practice the large risk population $k$ causes numerical problems since the initial value of $g(i)$ approaches zero, which may cause irregular running of the algorithm because of the limited accuracy of the computer's floating point arithmetic. To overcome this problem Waldmann's $L$-layer algorithm was used, which is a sophisticated reformulation of the Panjer recursion [21]. Model 3 and its variants were estimated using the bootstrap simulation technique, i.e., the observed empirical cost distributions of municipalities were used non-parametrically in the estimation. All the analyses were carried out in the Survo environment [22]. Some of the routines were self-implemented using C-programming language [23].

The cost distribution for inpatient care was positively skewed. Although not statistically proven, the log-normal distribution was considered to be a sufficient approximation of a true cost distribution (see figure 1).

### *4.4. Risk indicator*

The financial risk in each municipality was described by a risk indicator representing the cost variation in standardised form [9]. More specifically, the absolute cost fluctuation in a municipality was measured as the difference between the 95th and 5th percentiles of the corresponding aggregate cost distribution, and the risk indicator was then attained by dividing the absolute fluctuation by the expected value of the cost distribution. This kind of risk indicator is closely related to the traditional coefficient of variation, but is less sensitive to

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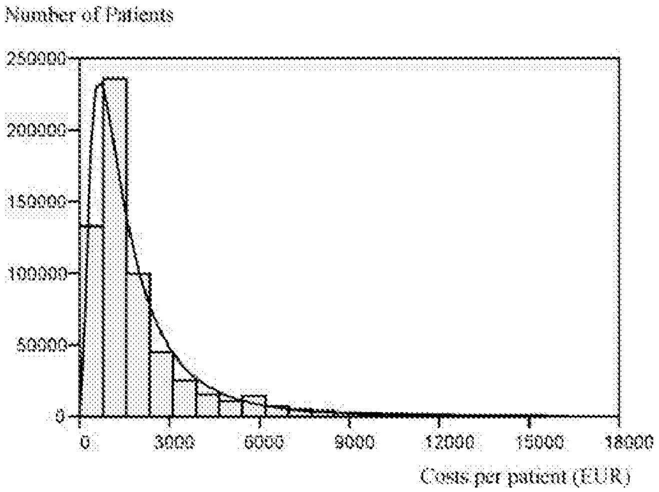


Figure 1. Patients' cost distribution relative to the fit of the log-normal distribution.

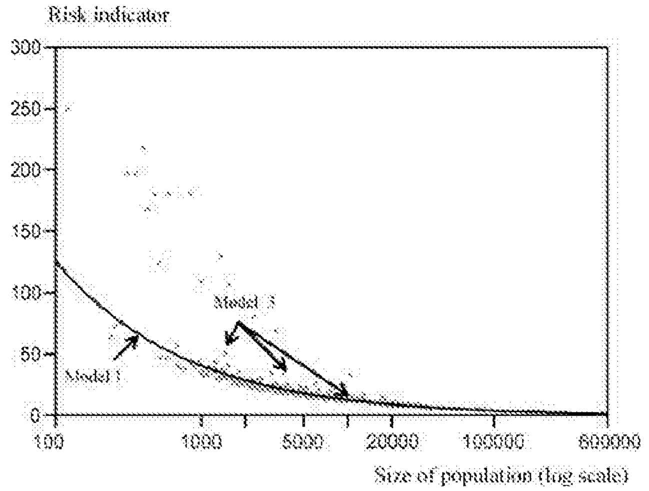


Figure 2. Comparison of results of the pure theoretical model and the non-parametric model.

Table 3
Comparison of results of the parametric and non-parametric models.

| | Size of population | Number of municipalities | DRG based prices/inpatient care, mean of risk indicator (%) | | | Difference (%) | |
|---|---|---|---|---|---|---|---|
| | | | Parametric model 1 | Parametric model 2 | Non-parametric model 3 | Model 3 − model 1 | Model 3 − model 2 |
| A | <1000 | 23 | 56.7 | 101.9 | 110.0 | 53.3 | 8.1 |
| B | 1000–2000 | 65 | 32.9 | 36.3 | 40.7 | 7.8 | 4.3 |
| C | 2000–5000 | 145 | 22.8 | 22.6 | 27.3 | 4.5 | 4.7 |
| D | 5000–10 000 | 111 | 15.5 | 15.2 | 18.8 | 3.3 | 3.6 |
| E | 10 000–20 000 | 59 | 11.2 | 11.9 | 15.5 | 4.3 | 3.6 |
| F | >20 000 | 49 | 6.6 | 6.6 | 8.7 | 2.1 | 2.1 |

the exceptional tails of cost distribution, since 10% of the most extreme values are discarded.

To compare the statistical significance of similarity between risk indicators obtained from different models and cases, the Wilcoxon matched-pairs signed-ranks test was used. The distributions of risk indicators were unknown and the estimated risks for the same municipality not independent.

## 5. Results

The results from the parametric and non-parametric models (1–3) are compared in table 3. For the sake of space and simplicity, the results of all 452 municipalities are given using the means of risk indicators calculated for various municipality groups (A–F). The association between the size of the municipality and financial risk was clear. In municipalities of less than 20 000 inhabitants the financial risk seemed to be substantial in terms of its impact on the budget of specialised care for an individual municipality.

The risk indicators seemed to be consistent across the parametric (models 1 and 2) and non-parametric (model 3) methods (table 3). In the municipalities of over 20 000 inhabitants the mean differences were practically negligible. For small municipalities (<20 000 inhabitants) the results of models 2 and 3 were not identical, probably because the expected number of patients more often differs from the national average than in the larger municipalities.

The results of models 1–3 for somatic inpatient care are displayed in figure 2. The solid line represents the behaviour of risk indicator in risk populations of different sizes. The grey dots in the figure 2 are the risk indicator estimates obtained from model 3 for each municipality. The risk indicator estimates seemed to be systematically higher for model 3 than for model 1 (figure 2, table 3). According to the Wilcoxon matched-pairs signed-ranks test, systematic differences were statistically significant (table 7).

The non-parametric bootstrapping method used in model 3 took better into account the variations in cost distributions, while the parametric assumptions for cost distribution (log-normal distribution for models 1 and 2) seemed to lead to a slight underestimation of financial risk in this data. Thus the rest of the results are based on model 3 (non-parametric bootstrap simulations).

The DRG based payment schemes protected the municipalities better against financial risk compared to per bed-day prices (table 4, cases 2 − 1). The difference between the risk indicators were significant, as in all other cases compared (see table 7). According to risk indicators, the total financial risk was over 4% higher on average if bed-day prices were used, e.g., in group C which includes most of municipalities (table 4). However, although the DRG based payment generally reduced the financial risk, there were some municipalities (42 examples of 452) in which the financial risk was higher in the case of DRG based prices (not reported).

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Table 4
Comparison of the results of different pricing systems with and without outpatient care.

| | Size of population | Number of manicipalities | Mean of risk indicator (%) Case 1 DRG based prices + outpatient care | Case 2 Bed-day prices + outpatient care | Difference (2 − 1) (%) | Mean of risk indicator (%) Case 3 DRG based prices (inpatient care only) | Case 4 Bed-day prices (inpatient care only) | Difference (4 − 3) (%) | Mean of risk indicator (%) Case 5 Bed-day prices + psychiatry (inpatient care only) | Difference (5 − 4) (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| A | <1000 | 23 | 95 | 103 | 7.9 | 110 | 114 | 4.3 | 123 | 12.6 |
| B | 1000–2000 | 65 | 38 | 45 | 6.9 | 41 | 48 | 7.2 | 77 | 28.7 |
| C | 2000–5000 | 145 | 25 | 29 | 4.4 | 27 | 32 | 4.7 | 60 | 27.9 |
| D | 5000–10 000 | 111 | 17 | 20 | 3.3 | 19 | 22 | 3.4 | 44 | 21.5 |
| E | 10 000–20 000 | 59 | 14 | 17 | 2.6 | 16 | 18 | 2.6 | 34 | 15.6 |
| F | >20 000 | 49 | 8 | 9 | 1.7 | 9 | 10 | 1.7 | 20 | 9.3 |

Table 5
The results from the example municipalities.

| An example municipality | Population | The netbudget of health care (EUR) | DRG based prices + outpatient care Risk indicator (%) | Average costs in somatic care (EUR) | A 5% risk over average costs (EUR) (in specialised care) | Potential fluctuation of total budget (%) | A 25% risk over average costs (EUR) (in specialised care) | Potential fluctuation of total budget (%) |
|---|---|---|---|---|---|---|---|---|
| Askainen | 918 | 737 460 | 78.1 | 396 984 | 175 505 | 23.8 | 57 678 | 7.8 |
| Jaala | 1995 | 1 849 033 | 25.8 | 669 411 | 88 038 | 4.8 | 35 199 | 1.9 |
| Isokyrö | 5207 | 5 905 606 | 19.7 | 1 886 075 | 197 737 | 3.3 | 72 318 | 1.2 |
| Kauhajoki | 15 028 | 14 136 339 | 10.9 | 4 543 566 | 253 164 | 1.8 | 98 147 | 0.7 |
| Kuusankoski | 20 835 | 19 498 088 | 9.7 | 6 702 452 | 327 872 | 1.7 | 134 372 | 0.7 |
| Joensuu | 51 514 | 43 323 274 | 7.7 | 17 542 605 | 704 691 | 1.6 | 263 532 | 0.6 |
| Helsinki | 511 123 | 607 337 546 | 2.0 | 157 032 053 | 1 566 252 | 0.3 | 620 911 | 0.1 |

Table 6
Comparison of the results using different cost limits for individual patients.

| | Size of population | Number of municipalities | DRG based prices + outpatient care Case 1 Mean of risk indicator (%) | Case 6 (limit 51 000 EUR) Difference (1 − 6) (%) | Case 7 (limit 34 000 EUR) Difference (1 − 7) (%) | Case 8 (limit 16 700 EUR) Difference (1 − 8) (%) |
|---|---|---|---|---|---|---|
| A | <1000 | 23 | 95 | 0.6 | 2.0 | 5.5 |
| B | 1000–2000 | 65 | 38 | 0.7 | 1.2 | 2.6 |
| C | 2000–5000 | 145 | 25 | 1.2 | 1.4 | 2.2 |
| D | 5000–10 000 | 111 | 17 | 0.7 | 0.9 | 1.5 |
| E | 10 000–20 000 | 59 | 14 | 0.9 | 1.2 | 1.9 |
| F | >20 000 | 49 | 8 | 0.5 | 0.7 | 1.0 |

The financial risk involved in cases of inpatient care without outpatient care were explored separately (table 4, cases 4−3). As can be seen from table 4, the average risk indicators were slightly higher in the model using only inpatient care. However, this risk increase due to removing a large number of 'cheaper' outpatient visits from the analyses did not change the main results, because the uses of inpatient and outpatient care are highly correlated. Those individuals who use a lot of inpatient care, also use outpatient care.

The most striking result was the increase in the magnitude of the financial risk in inpatient care when psychiatric patients were included in the simulation. Compared to somatic care alone (cases 5 − 4) (table 4), the financial risk increased 22% in the case of bed-day prices in group C. Another interesting finding was that financial risk also increased substantially in groups E and F, which represent the municipalities with over 10 000 inhabitants.

The example municipalities and their total health care net budgets were chosen randomly from different population groups to demonstrate the implication of the results (table 5). The net budget was equivalent to the total costs covered by municipalities (user charges are extracted from the total budget). In this interpretation the total budget presents the average expected budget. For example, in Askainen (a municipality of under 1000 inhabitants), there is a 5% probability that the total health care costs exceed the predicted (average) costs by more than 19.2% because of the financial risk; with 25% probability the total costs surpass the average expected costs by 7.3% (58 192 EUR). On the other hand, in the biggest municipality of Helsinki (the capital city) there is a 5% probability that the budgets are underestimated by more than 1.5 million EUR, but now the effect in the total health care budget is negligible (0.3%).

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Table 7
The results of the Wilcoxon matched-pairs signed-ranks test.

| Testing the difference between the risk indicators | $Z^a$ | $P$ |
|---|---|---|
| Table 3 | | |
| Type 3 model – type 1 model | 15.51 | $p < 0.0001$ |
| Type 3 model – type 2 model | 17.35 | $p < 0.0001$ |
| (Table 4) | | |
| Case 2 – case 1 | 15.05 | $p < 0.0001$ |
| Case 4 – case 3 | 15.06 | $p < 0.0001$ |
| Case 5 – case 4 | 17.25 | $p < 0.0001$ |
| (Table 6) | | |
| Case 1 – case 6 | 4.525 | $p < 0.0001$ |
| Case 1 – case 7 | 5.963 | $p < 0.0001$ |
| Case 1 – case 8 | 14.49 | $p < 0.0001$ |

[a] $Z$ is a normal approximation for a test statistic $W$ ($Z$ is distributed as $N$ (0,1)).

The study objectives included estimating the ability of the existing treatment cost limits (16 700–51 000 EUR) to reduce the random financial risk (table 6, cases $1-6$, $1-7$, $1-8$). The results show that the cost limits reduced the risk very slightly, even at the 16 700 EUR limit (cases $1-8$) (see also table 7). Changing the hospital pricing system (from bed-day based to DRG based) seemed to affect the random risk more than the current risk balancing system. However, in very costly individual cases the current system may protect small municipalities from total bankruptcy, but the system is not very effective in balancing the total random variation in costs.

## 6. Conclusions

As expected, in the Finnish hospital care system the size of the municipality is the main cause of uncertainty in total costs. However, although the introduction of DRG related pricing systems would appear to decrease the municipalities' financial risk compared to bed-day pricing systems, the effect of the pricing system on the financial risk was only modest. In addition, the results revealed that the current risk management system using payment limits for high-cost patients does not effectively reduce the total risk.

The Finnish state subsidy system was designed to balance the financial risk due to the need of health services. However, over the 1990s the share of state subsidies in total municipal health care financing decreased from about 50 to 20%. This means that small municipalities, in particular, have been bearing more risk than before. The smallest municipalities should therefore consider new organisational arrangements to solve the problem of the potential fluctuations of their health care budget due to cost variation in specialised care. Consequently, the Finnish hospital financing system needs to include other mechanisms than DRG pricing or cost limits to ensure effective pooling of financial risks among the small municipalities.

Small municipalities could seek protect in against financial risk by using contracts or creating bigger purchasing organisations. The specific contracts should cover the uncertain events, i.e., also take into account the random variation in the incidence of illness [15]. Alternatively, the contracts for small municipalities could be made for longer periods (e.g., several years). Larger administrative units pooling the risks of specialised care, especially psychiatric care, could be organised. In recent years some hospital districts have piloted contract controlled budgeting where individual or groups of municipalities control the hospital production in their hospital district using detailed agreements on costs and anticipated utilisation of hospital care. The contracts usually include estimates of the need of specialised services and their prices, or of total costs, as well as specific cost control of specialised services in separate municipalities and incentives to restrict rising costs, e.g., via quotas or price limits. However, these arrangements remain in the experimental stage.

Risk sharing has been one of the problems of DRG based hospital financing studied in the US Medicare system [17,24]. This problem in the Finnish context is somewhat different, however due to system specific features. The US Medicare is the largest single purchaser of hospital care in the USA, whereas the most Finnish municipalities are very small units. Moreover, Medicare regulates hospital production using DRG based prices, while the Finnish monopoly hospital districts are allowed to create their own pricing policy. Consequently, the refinements and outlier rules of DRG based pricing are developed to reduce the risk of hospitals and decrease patient selection in the US Medicare [25,26].

Although DRG based financing cannot by itself be an adequate solution for the problem of financial risk in Finland, DRG based prices could be useful for municipalities for many other reasons. For example, being a standardised system, DRG based prices allow direct comparison of prices, while cost information on cases using DRG related prices may help municipalities to budget for incoming costs more accurately [27]. On the other hand, hospitals which are inefficient compared to those which are able to produce at average costs would lose money and could be tempted to reduce their treatment intensity if DRG based prices were to be used, as would those hospitals (e.g., university hospitals in Finland) whose case-mix due to a hierarchical hospital system is more severe than average.

The parametric and non-parametric methods were compared in the estimation of financial risk of a municipality in order to explore the potentials of aggregate costs approach as a tool for health care management. In this data the non-parametric bootstrap simulation technique was found to be more appropriate than the models based on more restrictive parametric assumptions. However, the bootsrapping approach also has its own pitfalls, especially in small samples, where more advanced techniques (bias-corrected) are required. Nevertheless, similar techniques could be applied to yield distributions for various statistical estimators for cost data, for example, the resource consumption of uncommon DRG-groups which include relatively few observations and skewed multi-peak distributions.

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