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Jenni Pääkkönen

Timo Seppälä

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Jenni Pääkkönen, Government Institute for Economic Research (VATT)
Timo Seppälä, Government Institute for Economic Research (VATT)

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Abstract

This paper evaluates the determinants of quality - cost relationship in primary health care. We first summarize information from various indicators of care by principal component analysis (PCA), effectively producing quality of care indicators: *accessibility*, *coverage* and *allocative efficiency*. We then regress the costs of care against these indicators to evaluate their relationship. Our results suggest that PCA may be used to produce quality of care indicators. Furthermore, the relationship between the costs and quality of care is complex. Better accessibility is reflected in higher costs, whereas the efficient allocation of resources will bring some cost savings.

Key words: Quality of care, principal component analysis

JEL classification numbers: C38, H40, H51

Tiivistelmä

Tässä tutkimuksessa arvioidaan laadun ja kustannusten välistä yhteyttä perusterveydenhuollossa. Useiden perusterveydenhuollon mittareiden sisältämä informaatio tiivistetään ensimmäisessä vaiheessa pääkomponenttianalyysillä kolmeksi laatua mittaavaksi indikaattoriksi: saatavuudeksi, kattavuudeksi ja palveluiden allokatiiviseksi tehokkuudeksi. Toisessa vaiheessa perusterveydenhuollon yksikkökustannuksia selitetään pääkomponenttianalyysin tuottamilla indikaattoreilla ja arvioidaan, millainen yhteys kustannusten ja laadun eri ulottuvuuksien välillä on. Tutkimuksen tulokset osoittavat, että pääkomponenttianalyysiä voidaan käyttää rakentamaan laatuindikaattoreita. Lisäksi havaitaan, että kustannusten ja laadun välinen yhteys on monimutkainen. Parempi saatavuus on yhteydessä korkeampiin yksikkökustannuksiin, mutta palvelujen tehokkaampi kohdentaminen voi toisaalta tuottaa kustannussäästöjä.

Asiasanat: Terveydenhuollon laatu, pääkomponenttianalyysi

JEL-luokittelu: C38, H40, H51

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1 Introduction

The main task of a public health care system is to maintain and yield health among the citizens. However, government budgets are tight and the increase in health care expenses together with aging does not help to consolidate the budgets.[1] Decision makers may be able to minimize the increase in health care expenses by allocating resources efficiently.[2] However, policies are not alike: some cost-saving policies may harm the quality of care, while other policies may leave quality intact. To evaluate the influence of cost-savings on quality, one needs first a measurement of quality, and second, the relationship between costs and quality should be verified.

Most health economic research focusing on quality-cost issues has concentrated on *fragments* of health care (e.g. cardiac diseases, diabetes treatments), whereas given the weak economic prospects of governments, one should rather study the possibility of revealing a link between quality and costs at the *system level.* In this paper, we attempt to measure the quality of care at the system level. We also evaluate whether costs are systematically associated with quality. Finnish data from primary health care facilitate the contemplation of these issues empirically.

A review of the literature reveals several definitions of the quality of care (e.g. Lohr, 1990; Donabedian, 1988; Campbell et al., 2000).[3] However, some of these definitions, while explicit, are not easily operationalized in practice. For this reason, we rely on a survey by Campbell et al. (2000), which concluded that attributes such as accessibility, effectiveness, efficiency

[1] For discussion see Leibfritz et al. (1995), Seshamani and Gray (2004) and Stearns and Norton (2004).

[2] Chassin and Galvin (1998) suggested that improving quality by fixing overuse or misuse problems allows simultaneous cost decreases.

[3] For example, Donabedian (1988) proposed a system-based, three-pillar framework, where one should distinguish between the structure of a health care system (structure), the actual care given (process) and the effects of care on the health status (outcomes). For studies that aim to evaluate the quality of care at the patient level or as disease-outcome pairs, see Wray et al. (1995), Sloan et al. (2001) and Valentine et al. (2008). For studies aiming to reduce multidimensional quality to a unidimensional construct of latent quality, see Casparie et al. (1997) and Lee et al. (2000).

and equity are the main dimensions of quality of care. In particular, they suggested that at the societal level the quality of care is the ability to access effective care on an efficient and equitable basis in order to optimize health benefits for the whole population.

However, measuring unobserved quality is not without problems. Freeman (2002) named several technical problems with indicator selection that a researcher must overcome: the availability, validity and reliability of data; confounding factors; and problems with robustness, sensitivity and specificity. According to McClellan and Staiger (1999, 2000), the main limitation of quality indicators concerns their imprecise measurement, i.e. indicators are likely to incorporate a substantial amount of noise, or the outcomes may be influenced by factors unrelated to the quality of care. Furthermore, the multidimensionality of quality requires a set of indicators to be used to build *a single* quality indicator. Therefore, since quality measurement is tedious, most of the literature assumes that quality is exogenous and not correlated with costs or the output. However, as demonstrated by Braeutigam and Pauly (1986) and Gertler and Waldman (1992), the cost functions exhibit severe biases if they are not adjusted for endogenous quality.

Concluding from these studies, we hypothesize that the quality of care may be multidimensional in its attributes, whereby a wide set of macro indicators are explored to reveal its dimensions. Since such an approach is likely to result in the indicator failures discussed by previous authors, we make use of a method that is relatively robust to these failures.

In this paper, we utilize a novel method to examine the quality of care by exploiting principal component analysis (PCA) in order to summarize information from various health and health–related indicators. The great variety of measures, all carrying information on the quality of primary health care, enables the use of PCA to explore which indicators best explain the variation in the interpreted quality components. We draw from previous studies in interpreting the indicators in terms of the dimensions of quality and then compare our estimated dimensions with production costs to identify the relationship between quality and costs.[4]

To address these aims, we use national panel data from more than 300 Finnish municipalities over several years. The main benefit in using these data is that Finnish administrative data allow us to respond to the criticism and concerns raised by previous authors (e.g. McClellan and Staiger 1999, 2000; Freeman, 2002). Firstly, Finnish data incorporate numerous measures of the health status of the citizens and health care resources as indicators facilitating the measurement of quality. Secondly, with municipal–level data we can make use of socio-economic factors (e.g. demographics) to control for their influence on the outcomes, i.e. we can control for confounding factors by introducing risk-adjusting indicators. To validate our findings, we perform robustness checks. This study yields a tractable way to search for indicators whose establishment, use, and monitoring can be very helpful in intensifying and steering the public health care system.

The main contribution of this study is assessing the problem of measuring quality. Our results suggest that our indicator data, summarized by four principal components, incorporate three dimensions of the quality of care, namely (equal) accessibility, coverage and allocative efficiency, together with a risk-adjusting component. These findings depart from those of McClellan and Staiger (1999, 2000), since constructing only *one* quality indicator might not be enough at the system level. Making use of the interpretation for the set of indicators with quality content, an important finding in this study is that the accessibility dimension of the quality of care is the main factor explaining the observed variation between municipalities.

Moreover, after using the estimated quality of care indicators as outcomes in a cost function, we find that costs are related to the quality of care in a

[4]We are familiar with the fact that one can derive other interpretations for our estimated quality indicators, for instance, in the context of demand and supply. However, we believe these differences are mainly nuances and do not alter the results concerning the cost estimation.

rather complex manner. On the one hand, we find that better *accessibility* is reflected in higher costs. On the other hand, *allocative efficiency* is negatively related to the costs of care, although there is little variation *between* municipalities in this dimension. Here, our results verify those of Gertler and Waldman (1992) in that if the dimensions attributed to quality of care were not controlled for, the cost efficiency of health sector would be erroneously measured, making the results concerning the (in-) efficiency biased.

This paper is structured as follows. Section 2 defines the quality of care and its indicators, while the methods are reviewed in section 3. Section 4 presents the results from principal component analysis and cost efficiency evaluation, and section 5 discusses the merits of these findings.

2 Quality of care indicators

By definition, quality is a latent variable that is not directly observed but is manifested in a number of observable indicators. We thus collect information on a number of indicators related to health care services and study them with principal component analysis to determine what part of the variation in the data is due to indicators that can be interpreted as having a quality component. Further, we hypothesize that at the system (population) level the quality of care is multidimensional, and these dimensions can be named as accessibility, allocative efficiency and coverage. However, it is not clear from the outset which one dominates or whether all these dimensions are present in our data.

As care for the whole population may conflict with care for individual patients, we emphasize the system (population) level in describing quality and in the choice of indicators. *Equal accessibility* corresponds to different sub-populations and users all being served, whereby it is one measure of horizontal equity (age & disease pair). C*overage* corresponds to citizens across the country all being served, i.e., this quality indicator measures horizontal equity in the spatial dimension. However, there is no reason why equal accessibility and coverage might not be merged into one dimension, which remains to be tested in our empirical analysis. *Allocative efficiency* corresponds to the existence of a tendency for vertical equity so that those with greater need also have better access to care.[5] Yet, as suggested by Chassin and Galvin (1998), efficiency also means that there is no misuse, overuse or underuse of care - irrespective whether it is measured across a country or sub-populations. If a municipality focuses on procedures whereby institutional care is substituted by less intensive care, such as informal care, one can name the last component not just as efficiency but allocative efficiency, since resources are targeted (prioritized) at those with a greater need.

To assess quality, we here use annual health indicator data mainly on primary health care from 342 Finnish municipalities for time span from 2000 to 2006/2009.[6] The data are available at national database SOTKAnet (SOTKAnet, 2011), except for data on wages and on the price index for public expenditure, which are available from the registries of Statistics Finland (Statistics Finland 2011a). Two sets of exclusions took place. The Åland Islands was excluded, since the inhabitants use both Finnish and Swedish health care systems, making the Finnish registry data unreliable with respect to the population. Also, municipalities in the Kainuu region were excluded, since they co-operate in public health care provision, causing the municipality level data filed in the registry to be unreliable. After exclusions, we are left with 318 spatially independent observations (municipalities). Moreover, since data on inputs are only available up to 2006, models including these indicators are estimated from 2000 to 2006.

We have 51 indicators in total, of which 27 indicators can be interpreted to measure the health outcomes or demand for health care, 13 to measure

[5]Campbell et al. (2000) divided equity of care to horizontal equity (equal accessibility to effective care for all users) and vertical equity (greater access to effective care for those with more need).

[6]We focus on primary health care, since specialized health care is organized in larger joint municipal boards (e.g. central hospitals).

resources and inputs and the remaining 11 to describe the socio-economic and demographic conditions of a municipality as controls for possible heterogeneity and confounding factors. To take into account the differences in demographics across Finland, we also make use of a number of age and sex standardized indicators, while for convenience most of the indicators are measured in per capita terms. We further group the indicators according to their relationship with the quality of care into four broad categories that are not necessarily mutually exclusive. We assume that control variables are not related to the quality of care per se, although they might influence the demand of care or resources available for care.

At the system level, very few indicators exist that are interpretable as reflecting the quality of care *directly* as an outcome of the care (e.g. mortality), as a measure of the service portfolio (e.g. service housing with 24-hour assistance for the elderly) or as an indicator for opting out from public care due to quality deficiencies (e.g. reimbursement for visits to private physicians). Most of the indicators are *indirect* quality indicators, which are further grouped into *accessibility* and *coverage*. The indicators that fall in the accessibility group typically indicate the availability of care (e.g. hospital care, patients per 1000 inhabitants). All resource indicators, such as the number of practical nurses in primary health care, fall in the category measuring coverage. The last category reflects *risk adjustment* (and the case mix), such as diseases related to substance abuse or the unemployment rate. The remaining control variables are relatively loosely tied to the quality of care and are best described as controls for the *budget* (e.g. loans) or *age structure* (e.g. population aged 15-64) and other demographics.

One novelty in our approach comes from the use of entitlement data, whereby we further scrutinize these indicators. Entitlement indicators exist for different age and disease groups, although for younger cohorts some diseases are rare and only the aggregates can be used.[7] According to the

[7]These indicators come from the Social Insurance Institution of Finland (Kela), which

Social Insurance Institution of Finland, the entitlement to special refunds on medicines means that the person in question has some serious or long–term illness requiring medication (e.g. coronary heart disease or diabetes) (Kela, 2012). Each illness has its own criteria upon which entitlement is granted, and the application always requires a statement from a specialist. However, since the entitlement funding comes from the central government body and not from the municipal budget, neither general practitioners nor specialists have an incentive to withhold patients from such status. Since the criteria for the entitlement to special refunds on medicines are strict, yet transparent, these indicators give us a homogeneous grouping of diseases. Therefore, the entitlement indicators enable us to truly compare like with like in terms of the prevalence and complexity of illness (the case mix). This merits the interpretation of entitlements as a homogeneous grouping, i.e. quality–adjusted output, containing information on accessibility.

To evaluate the relationship between costs and quality, the data include the costs of care measured as the net expenditure on primary health care, including dental care. According to Statistics Finland, net expenditure is obtained by subtracting the operating income from operating costs (Statistics Finland, 2011a). The health status indicator (i.e. morbidity index) created by the Social Insurance Institution of Finland provides a benchmark for our quality indicators to facilitate the comparison and discussion.[8] All 51 variables used to estimate the static factor together with the data on costs, wages and morbidity are specified in Appendix A.

is responsible for providing social security benefits for the residents of Finland.

[8]According to the definition given by the Social Insurance Institution of Finland, the morbidity index is based on three register variables: mortality, the proportion of disability pension recipients in the working-age population and the proportion of people entitled to special refunds on medicines in the total population.

3 Methods

Our analyses proceed as follows. The first question we address is how to capture the quality of health care from a set of indirect indicators. While the direct measurement of the system-level quality is unfeasible due to the lack of specific indicators, there are ways to assess quality indirectly from a set of different indicators that can be defined as having quality components. Then, having defined the dimensions of the quality of care, we assess their relationship with the costs in a fixed effects model.

Our methodological response to the concerns raised in the literature builds on the tradition of factor analysis, and a principal component analysis (PCA) in particular.[9] PCA aims to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data (Jolliffe, 2002). The principal components methodology is applied to the variance structure of the indicator variables, and is ideal for descriptive purposes. The virtue of PCA is that while some of the indicators are weakly linked to quality of care or imprecisely measured, the method will limit the influence of noise on the outcomes.

We closely follow McClellan and Staiger (1999, 2000) in interpreting our approach, although we depart in one key aspect. While we also take a bunch of data and filter the noise from it, the outcome of our procedure is from one to three new variables that represent different dimensions of the quality of care. That is, while previous research has tried to summarize the information into *one* indicator, we believe the multidimensionality of quality might be manifested in more than one principal component, as explained in section 2. Formally, the approach will have the following preliminaries and set-up.

[9]Principal component analysis is often presented as a special case of factor analysis, since the PCs can be used to estimate the factors. For discussion see Jolliffe (2002), Chapter 7.

Principal component analysis

Assume we have a $(p \times 1)$ random vector of observed indicators X, with mean μ and covariance matrix Σ , each indicator related to the non-observed quality of care η as in the classical measurement error model $X = \beta\eta + \epsilon$ where ϵ is the measurement error. The idea is that each observed indicator contains information on the quality of care and some noise. Now, since this quality may have more than one dimension, the relationship between the indicators and the quality is $X = \beta_1\eta_1 + \beta_2\eta_2 + ... + \beta_n\eta_n + \epsilon$. Using the categorization described in section 2, our aim is to interpret the principal components (PCs) with these terms.

One way to determine the quality of care is to write a general factor model for a pooled model expressed as

$$X = \Lambda F + \varepsilon, \tag{1}$$

where Λ is a $(p \times m)$ matrix of *factor loadings,* each λ_{ij} representing the loading of the ith variable on the jth factor, F is a $(m \times 1)$ vector of *common factors,* and ε is a $(p \times 1)$ vector of error terms. The idea is to capture the variation present in p random variables (X) with $m \ll p$ common factors (F). As we want to combine information from a relatively large number of indicators into a small number of factors, we are interested in the proportion of sample variance contributed by the various factors. We then use ΛF to produce the principal components that approximate η – the quality dimensions.

The principal component solution can be obtained either from the sample covariance matrix or the sample correlation matrix.[10] We prefer the correlation matrix over the covariance matrix, because principal components that are obtained from the covariance matrix are sensitive to the units of mea-

[10]Since factor analysis is a well-known technique, we omit the presentation for the solution, which can be found in Johnson and Wichern (2002) or in Jolliffe (2002), among others.

surement of the elements of X. In particular, if the indicators are measured at different scales and have different variances, then those indicators with largest variances tend to dominate in the first PCs. It is apparent that the aforementioned facts hold true for our set of indicators, and hence use of the covariance matrix will be ruled out, leaving us with the correlation matrix.

Fixed effects cost model

In the second stage, we regress primary health care costs on estimated factors, which provide proxies for the dimensions of quality. We allow for individual fixed effects to control for other unobserved heterogeneity in the panel. If the quality of care were not modelled, the fixed effects would also include the unobserved quality of care.

Let us assume that the cost function is represented by a fixed effects model

$$c_{kt} = \alpha_k + \gamma' \eta_{kt} + \delta' z_{kt} + e_{kt}, \tag{2}$$

where c_{kt} are primary health care (operating) costs for municipality k, α_k are unobservable fixed effects other than quality indicators, η_{kt} are the quality indicators, z_{kt} are other observable characteristics, and e_{kt} is a random disturbance term. Our expenditure data reflect variable costs, since capital expenditure and fixed assets are excluded. Therefore, we approximate the short-term cost function.

We estimate three different, non-nested versions of the cost model. The benchmark model does not include any quality indicators, but it is a very simple cost model including a proxy for the wages, two standard outcomes and two control variables. In this model, the quality of care is treated as unobservable and incorporated in the fixed effects estimates. In the second version, instead of the standard outcomes, the quality component obtained from the sub-set of data is included in the model. Lastly, in the third version, quality component(s) from the extended set approximate the outcomes of health care.

Our indicators are expressed in per capita terms, whereby the capital of Finland (Helsinki) should not drive the results (because of being more than twice as big as the second largest city, Espoo). Therefore, Model (2) is also estimated in per capita terms.[11] Since the statistical properties of the generated variables, i.e. PCs, are generally not known, the estimated standard errors might also be inconsistent.[12] To mitigate the effect of this failure, we present bootstrapped standard errors.

Estimation procedures

Our estimation proceeds as follows. We first estimate the factor model with 27 indicators to identify which of the components the indicators having quality of care content seem to have greatest impact on. Second, we add other variables related to health care (but not necessarily to its quality) to explore whether and how the components of interest react to this additional information. This is to say that we add measures of inputs and socio-economic and demographic variables to data. Then, having defined the dimensions of the quality of care, we assess their relationship with the costs in a fixed effects model.

4 Results

Principal component analysis

Model 1a (columns 2 and 3) in Table 1 presents the results from PCA. When exploring 27 indicators to identify 27 principal components, we find that the

[11] An additional reason for preferring the linear model is that one should incorporate interactions and second order terms in the trans-log cost function. In the presence of principal components this is not feasible, as they are orthogonal. Furthermore, the higher order polynomials of PCs might not necessarily have any meaningful interpretation. However, we acknowledge that estimating the cost model in per capita terms in effect imposes linear homogeneity.

[12] Pagan (1984) evaluated the econometric problems of using generated variables in a regression equation.

first 8 of the components explain two-thirds of the total sample variance. In addition, the rate of decrease in the explanatory fraction is rather rapid, as the first component explains 30%, the second 9% and the eight PC less than 4% of the variance.

	Model (1a)	
Component	Proportion, %	Cumulative prop., %
$pc1$	29.6	29.6
$pc2$	9.0	38.6
$pc3$	7.8	46.4
$pc4$	5.5	51.9
$pc5$	4.6	56.5
$pc6$	4.3	60.8
$pc7$	4.0	64.8
$pc8$	3.6	68.4

Table 1: Principal component analysis, N=2574

In order to interpret the PCs, one needs to evaluate the factor loadings. We are keen to determine which dimensions of quality (if any) are present in the PCs. Through the construction of the PC method, the first component captures most of the total sample variance, and hence it is of a natural focus of interest which variables obtain the highest loadings on it. Table 2 presents the highest factor loadings in absolute terms (the cut-off being ± 0.15)[13].

Three types of variables have high factor loadings on the first principal component (PC1). Firstly, the first PC has high factor loadings on the standard outputs of health care, i.e. hospital care and inpatient health care, which reflect the availability/accessibility of health care. Second, the prevalence of sickness in the population is well represented, as those entitled to special refunds on medicines and the number of disability pension recipients also have high factor loadings. Almost the *entire* population is represented here, as different age and disease groups are present in first PC, i.e., all age groups are *equally served.* As already discussed in section 2, since the en-

[13]According to Jolliffe (2002), no test for statistical significance exists. One plausible criterion is to report coefficients whose absolute value is greater than half of the maximum coefficient, i.e. 0.313/2.

titlement decision is based on the severity of the disease on the basis of a certificate issued by a specialist, the entitlement indicator reflects, from one point of view, the prevalence of severe (or long-term) diseases in the population, but also, from another point of view, the ability of the system to pinpoint those who are in need of a special refund status and medication.[14] Lastly, the two measures of the use of private care seem to be important variables in determining the first PC. Clearly, those who are less satisfied with public care, less inclined to wait to be served, or living in areas where public care availability is limited, opt to use the private health care partly at their own expense (willingness to pay).

Variable	Factor loading
Entitled to special refunds on medicines (ESRM), as % of aged 40-64	0.313
Inpatient primary health care, patients per 1000 inhabitants	0.287
ESRM: coronary heart disease, as % of aged 65 and over	0.276
Entitled to special refunds on medicines, as % of aged 25-39	0.275
Disability pension recipients: mental ..., as % of aged 16-64	0.274
Hospital care, patients per 1000 inhabitants	0.270
ESRM: asthma, as % of aged 65 and over	0.229
ESRM: psychosis, as % of aged 65 and over	0.224
ESRM: diabetes, as % of aged 65 and over	0.213
ESRM: hypertension, as % of aged 65 and over	0.212
Inpatient primary health care, care days per 1000 inhabitants	0.212
Visits in private dental care per 1000 inhabitants	-0.248
Reimbursement for visits to private physicians, recipients as % of t.p.	-0.258

Table 2: Factor loadings on the first principal component for Model (1a)

Next, we bring the resource and control variables under scrutinization, i.e. we add 24 extra variables to the data set. Given that we now have 51 variables present in data, the first PC appears to account for a reasonable

[14]One can speculate that if the system were of high quality, i.e. if all people in need of special reimbursement entitlement also received it, the variation between areas would not indicate differences in the quality of the system, but rather differences in the prevalence of a particular health problem. However, while this can hold true for some diseases, it certainly does not hold true for all of them. Most of diseases are such that their prevalence should be uniformly (age and sex adjustably) distributed between areas. Then, the differences between areas would reflect differences in the quality of care.

amount of variance, as it explains 20% of the total sample variance, while 11% of the sample variance is explained by the second PC (Table 11 in Appendix B). Nevertheless, adding more variables also introduces more 'noise' to data, whereby it is not necessary that all first PCs are closely related to (the quality of) health care.

Model (1b) Variable	Factor loading
Entitled to special refunds on medicines (ESRM), as % of aged 40-64	0.271
Inpatient primary health care, patients per 1000 inhabitants	0.263
Hospital care, patients per 1000 inhabitants	0.254
Disability pension recipients: mental ..., as % of aged 16-64	0.250
Entitled to special refunds on medicines, as % of aged 25-39	0.241
ESRM: coronary heart disease, as % of aged 65 and over	0.225
ESRM: psychosis, as % of aged 65 and over	0.203
ESRM: diabetes, as % of aged 65 and over	0.191
Population aged 65 and over as % of total population	0.181
Population aged 15-64 as % of total population	-0.183
Tax revenue, euros per capita	-0.210
Visits in private dental care per 1000 inhabitants	-0.210
Reimbursement for visits to private physicians, recipients as % of t.p.	-0.224

Table 3: Factor loadings on the first principal component for Model (1b)

To further asses the information content of the first PCs of Model (1a) and Model (1b), we compare them against each other. Evaluating the highest factor loadings of the first PC reveals that irrespective of the additional data, same variables seem to rank highly in forming the first PCs, as 10 out of 13 variables are the same as in Model (1a).[15] However, some differences appear as are emphasized in Table 3. A particularly interesting change is the appearance of demographics-related control variables in the set of variables that load the first PC (i.e. the share of working-aged in the total population and the share of retired in the total population). The presence

[15]If one were to use 0.14 as a cut-off, the list of interesting variables would include six extra variables (sign): population aged 65 and over (+), inpatient primary health care, care days per 1000 inhabitants (+), entitled to special refunds on medicines for hypertension (+) and on medicines for asthma (+), unemployment rate (+), and children aged 1-6 yrs in municipally funded day care (-). More detailed results are available from the authors upon request.

of the share of the working-aged is accompanied by *tax revenue*, as together they drive a municipality's budget. Second, most employees are entitled to occupational health care, whereby a high share of workforce and employment in particular will lower the demand for public health care. When retiring, the entitlement naturally vanishes, whereby the share of elderly in the population is positively related to the use of public care.

Irrespective of these interesting changes, our results for the first PC seem relatively robust. This is verified by the fact that PC1 of Model (1b) and PC1 of Model (1a) are very highly correlated (98), which suggests that they share exactly the same information content. Then, although typically with PCA less is more in terms of the number of variables, we prefer Model (1b) over Model (1a), as we are interested in different dimensions of the quality of care.[16] Hence, we concentrate on the PCs of Model (1b) in the subsequent analysis.

To summarize our findings thus far, it appears that in the first principal component the key determinants have a tight relationship with a quality that is attributed to the accessibility of public health care. Nevertheless, while the first component carries information on the equal accessibility of public health care, it also suggests that some patients opt out from the system either due to quality deficiencies or congestion.

The interpretation of subsequent components builds on the fact that each PC adds *new* information to the previous ones, since the PCs are orthogonal. In other words, if the first component measures the quality through accessibility, as seems to be the case, the subsequent components should measure other aspects of quality. Since not all of the 51 components are relevant, we concentrate on those components capturing the majority of the variation, i.e. components 1–4, which also are components that capture interesting quality

[16]The results presented by Bai and Ng (2002) suggest that the number of variables to construct the factor need not be extremely large for the principal components approach to yield precise estimates. Thus, the number of indicator variables in our analysis could be smaller.

attributes (See Appendix B, Tables 11–13).

With regards to the second component, it appears that the 12 highest ranking variables are all health care inputs and signal the importance of the coverage of health care. The thirteenth variable is a measure of entitlement to special refunds on diabetes medicines in the cohort aged 65 years and over, but it is less important than the others by a large margin. Therefore, it is clear that the second PC measures the input mix and the coverage of care.[17] Here we take an approach that greater coverage is an indication of greater quality. The third component, on the other hand, has high loadings on different measures of services that are closely associated with primary care, in particular on those social services geared to children and youths. Therefore, the third PC can be interpreted as a need for social assistance, and reflects *risk adjustment*. An implication is that the third PC includes no information on the quality of the health care per se.

Lastly, as the interpretation of the fourth PC is less clear, and the amount of variation it captures is also only 6% of the total sample variance, this is the final component we interpret. Firstly, the two demographic extremes are present in this component. The share of children and youths is present with a positive sign, while the share of elderly people is manifested with a negative sign. Second, the services geared to the elderly seem to dominate the fourth component, as there are several such indicators present in it. Their presence signals the extent of the service portfolio and the quality of care for the elderly (*support for informal care*, *inpatient care days* and *mortality*). In particular, the two extremes of intensity of care are present: informal care at home, where care is given by family members, relatives or friends, and inpatient care days in hospitals, with the elderly having the majority of care days. Since the two extremes for the intensity of care and for the age structure are present in the fourth component, it therefore reflects

[17]One could speculate whether the suggested input mix is optimal. This question, however, is out the scope of this paper.

care geared to the elderly, and the quality of municipalities' overall portfolio design in particular. For the sake of simplicity, we name this component allocative efficiency.

To summarize, our results indicate that the quality of care has three different quality dimensions: first, the (equal) accessibility of public health care; second, the coverage of public health care, and finally, the age-related/portfolio quality of care, i.e. allocative efficiency for short. The third PC seems to reflect risk adjustment and is not a signal of quality.

We perform a further check to evaluate the robustness of the above findings.[18] We exclude the entitlement indicators from the data and build our analysis on data typically available to researchers. To simplify the comparisons, we only report the subsequent changes in the first four PCs as they appear, while more details are available from the authors upon request. The first three PCs experience minor changes and they are all highly correlated with the original PCs, the pairwise correlations being over 90 for respective pairs. The greatest number of changes appears in the fourth component, although the original and the robust PC are highly correlated (67.8). Since the entitlement indicators are not present in the data, none of the 'robust' PCs can include any of them, but all other key indicators from Model (1b) are present.

The new variables present in the 'robust' PC1 all measure accessibility.[19] Clearly, they capture roughly the same information as the entitlement indicators, as manifested in the high correlation coefficient of the PCs. Virtually no change appears in the second PC, as the input variables also dominate the 'robust' PC2. This holds true with the third component as well, where only one new variable appears in the 'robust' PC.[20] The majority of changes

[18] One obvious robustness check is to include the costs of care in the data and redo the PCA. As first components of Model (1b) were not influenced by this change, the results are not reported here.

[19] Presented in order of importance, the variables are: Inpatient primary health care days; Unemployment rate; Dental care patients in health centres; Children aged 1-6 in municipally funded day care and Outpatient physician visits in primary health care.

[20] *Disability pension for mental and behavioural disorders recipients* displaces Outpatient

appear in the fourth component, as in the absence of entitlement data, indicators of socio-economic and demographic characteristics appear in the 'robust' PC4.[21] To summarize, perhaps with the exception of the fourth PC, the PCs are relatively robust to the exclusion of entitlement indicators. The majority of changes appear in the sense of a polarization, whereby the remaining key indicators gain more weight in forming the 'robust' PCs, while the other indicators become less meaningful.

Fixed effects cost model

A second stage is to evaluate the usefulness of the above findings and to examine the relationship between the quality of care dimensions and the costs of care. To this end we perform three straightforward regressions. As our benchmark regression (Model 2'), and to facilitate comparison, we regress the costs of primary health care on standard outputs (morbidity index, number of outpatient visits) and control variables (offenses against life and health, support for informal care). We then regress the costs of care on the PC1 of Model (1a) and on same controls as in our benchmark model. Lastly, we replace the outputs and controls with the first four PCs of Model (1b) and redo the analysis. The models also include approximated wages[22], a constant and a linear trend. Only those municipalities are included where we have an adequate number of observations to perform a meaningful analysis. The estimation results are presented in Table 5.[23]

visits in specialized health care.

[21]What exactly happens with the fourth PC is that it becomes more polarized in the sense that a few key indicators dominate it, while the rest have little weight on the PC. The dominant variables are those present in PC4 of Model (1b) accompanied by *Outpatient visits in specialized health care*, *Social assistance recipients* and *Population aged 15-64 as % of total population.*

[22]Wage data are available from 2008 onwards, while we approximate the wages for 2000–2007 by using the price index of public expenditure.

[23]Acknowledging Newhouse's (1987) discussion on raw data versus log transformation, we also estimated Model (2b) with log cost, but this resulted in only minor changes in the results. After log transformation, coverage would also be statistically significantly, although negatively, related to costs. Furthermore, including PC2 in the cost model is perhaps a little unconventional, since it reflects the input mix, but we are testing the value added of our analysis rather than seeking the best cost model.

Variables	Model (2')	Model (2a)	Model (2b)
PC1 of Model (1a)	–	4.66 (.753)	–
PC1 of Model (1b)	–	–	5.08 (.701)
PC2 of Model (1b)	–	–	.497 (.439)
PC3 of Model (1b)	–	–	1.21 (.383)
PC4 of Model (1b)	–	–	−.829 (.444)
Wage	346.4 (90.9)	305.6 (88.1)	249.5 (95.7)
Control Variables			
Morbidity index	−1.06 (.723)	–	–
Outpatient physician visits	.005 (.005)	–	–
Offenses against life and health	.270 (.884)	.676 (.886)	–
Support for informal care	2.13 (1.50)	−.479 (1.30)	–
c	370.5 (46.6)	115.9 (36.30)	−23.8 (52.2)
trend	26.8 (.783)	25.9 (.772)	27.6 (1.28)
N	1522	1522	1522
Groups	246	246	246
R-squared	0.18	0.60	0.67

Table 4: Estimation results. Bootstrapped standard errors in parentheses (Models 2'–2b).

Let us first consider Model (2') as a starting point for our analysis. None of the standard outputs or controls is statistically significant, not even morbidity index. In this model, costs are only explained by wages, a constant and a trend. The model is under-identified and probably yields biased results. Incorporating the first PC in the model (Model 2a) changes the results.[24] Namely, while neither of the control variables are statistically significant, the first PC is. This finding suggests that in summarizing the information on

[24] The Hausman specification test suggests that, compared with a random effects model, a fixed effects model is an appropriate model specification. In addition, when we estimated a two-way fixed effects model, that is, included the year dummies instead of a time trend, the dummies seemed to pick a linear trend. Hence, to avoid unnecessary complications, we prefer to present the results yielded by a standard fixed effects model with a linear trend instead of a two-way fixed effects model.

care, performing PCA was meaningful.

In Model (2b), which is the quality-adjusted cost function the first principal component, the accessibility of care, is positively related to the costs of care, i.e. high costs and high accessibility seem to go hand in hand. Second, the coverage quality (PC2) is not related to costs. Given that coverage reflects inputs and we already have wages in the model, this finding is as expected. Third, the risk adjustment (PC3) is positively related to costs, while the portfolio and care geared to the elderly (PC4) is negatively related to costs.

Since all PCs are measured with the same range, that is, as an index from 0 to 100, it is easy to compare the estimates with each other. The largest savings could be achieved by reducing the accessibility of care, while cost savings could also be achieved by more efficient allocation of resources in the care for the elderly. In particular, as long as informal care and inpatient care are substitutes, allocating more resources to informal care and less to institutional care makes sense. However, if these savings come from keeping elderly patients in informal care when they should be receiving more intensive, institutional care, then such cost savings are simply a cost reallocation from the present to the future and make no sense. There is room for savings only over- or misuse of intensive care are occurring.

Since the models are not nested, it is difficult to evaluate how much value added the PCs really had in terms of evaluating inefficiency.[25] One way to evaluate this is to produce the fixed effects from all three models. In the benchmark model, the fixed effects estimate should include the latent quality, while its influence is deducted from fixed effects of Models (2a) and (2b) in particular. Therefore, since the fixed effects are not directly comparable, we rank the municipalities according to them and then compare the deciles.

[25]While comparison of the models that are non-nested is not feasible with standard tests, we estimated a larger model including all variables from Models (2b) and (2') with the exception of the morbidity index, which was excluded due to its high correlation with PC1. These results confirm that Model (2b) is closer to the true model than Model (2').

It appears that 78% of the municipalities shift from one decile to another when comparing the fixed effects produced by Model (2') to those of Model (2b). Some municipalities experience rather strong transitions, as is the case for Espoo (the second largest city) for example, which swings from the first decile (i.e. the most efficient) to the seventh decile after quality is accounted for. Changes are less radical when comparing Model (2b) with Model (2a), as half of the municipalities remain in their original decile and the biggest leaps and lapses are by 3 deciles. Nevertheless, using only the first PC is not enough to yield correct inferences regarding inefficiency.

To summarize, the results from Model (2b) indicate that using PCA to reduce the dimensionality when producing the quality components offers important insights into the relationship between the quality of care and its costs. Furthermore, if the variation in the information we interpret as quality is not controlled for, the efficiency estimates yield biased results, whereby some municipalities are displaced to the wrong group. From a policymaker's point of view, such shortcomings can be dangerous and lead to erroneous, potentially even harmful decisions.

5 Discussion

We aggregated information from various macro-level indicators of health care by means of factor analysis, effectively producing three quality of care indicators. We then regressed costs on the estimated factors and examined the relationship of accessibility, coverage and allocative efficiency with the costs. The relationship between costs and quality is more complex than previously thought: increases in accessibility can only be achieved together with increases in costs, while increases in allocative efficiency may potentially lead to reduced costs.

Our results clearly point out the importance and relevance of PCA when extracting information from macro-level indicators. Scrutinization of the first principal component suggests that the most important dimension of quality is the accessibility of care. Such an outcome is hardly surprising, as equal accessibility is perhaps the most important aspect of the quality of care, and the underlying reason for the publicly provided and funded health care in the first place. Therefore, we take it as a positive signal that different age and disease groups are equally represented in the first PC.

What policy implications do our results offer? From the policymakers' point of view, it is a telling sign that indicators of the use of private care are also present in the first component. It appears that people opt out of public care because of quality deficiencies or due to congestion or the inexistence of the public provision. Furthermore, its relationship with costs is positive, with better accessibility of care being reflected in higher costs. Our results also suggest that it is worth paying attention to the inputs in health care, although their relationship with the costs of care remains ambiguous. Lastly, our results indicate that by enhancing allocative efficiency, municipalities are able to achieve some cost savings. It also is a signal that the service portfolio will become easily dominated by those services that are geared towards the elderly. As the Finnish population is rapidly aging and the age-related demand for care is set to rise in the coming years, this is a weak signal of the age-related pressure on costs.

The results of the study are also applicable to other countries than Finland, as policymakers will need tools to tackle the increasing demand for health care and pressure on costs. The current paper facilitates the task by providing the audience with information on the indicators that should be concentrated on when evaluating the outcome of the health care system with the aim of hindering unnecessary cost increases. Finally, the issues addressed in this paper are not unique to health care, but similar problems arise in other (public) services. Our approach to address the problem is applicable to other fields as long as indicator data exist.

While our results are potentially very useful for those who wish to summarize information from various indicators to produce aa quality indicator, or any other, a caveat is in place. At the system level, very few indicators can be attributed as direct quality indicators, whereby the principal components (PCs) constructed from aggregate macro-level indicators are not as intimately tied to quality as one might want. In our case, instead of accessibility, coverage or allocative efficiency, one can derive other interpretations for these components, such as demand, supply and so on. Irrespective of whether one wishes to label the indicator as accessibility or, say, demand, it is important that these indicators effectively summarize information from various indicators, making the estimation of the cost model more efficient, as also shown in our results.

One avenue of future research could be an evaluation of the various indicators of health care with more disaggregated data. Moreover, if the data were available, variables that are more directly controlled by decision makers, such as preventive policies, would also be worth investigating. Such analysis would have important implications for economic policy-making.

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A Appendix: data

Tables 5–7 list the variables used to estimate the static factor. The variables are categorized according to their relationship with quality, that is, whether they measure quality directly (D) or indirectly (I). The latter are further categorized as measures for accessibility (A) and coverage (C) or risk adjustment (R). Those variables that are more loosely related to quality are either demographic controls (DC) or budget controls (BC). The source of the data is SOTKAnet, unless otherwise indicated. The number in parentheses specifies the ID code used in SOTKAnet.

Quality measures	Form
Disability pension: mental and behavioural disorders, as % of aged 16-64 (3218)	D
Outpatient physician visits in primary health care, per 1000 inhabitants (1552)	A/I
Outpatient visits in specialised health care, per 1000 inhabitants (1560)	A/I
Patients seen by a physician in primary health care, as % of tot. pop. (3224)	A/I
Dentist visits in health centres, per 1000 inhabitants (2397)	A/I
Inpatient primary health care, care days per 1000 inhabitants (1267)	A/I
Hospital care, patients per 1000 inhabitants (1256)	A/I
Inpatient primary health care, patients per 1000 inhabitants (1268)	A/I
Dental care patients in health centres, patients per 1000 inhabitants (1559)	A/I
Psychiatric inpatient care, care days per 1000 inhabitants (id:1263)	A/I
Diseases related to substance abuse: periods of care, as % of aged 15-24 (1279)	R
Entitled to special refunds on medicines (ESRM), as % of aged 0-15 (230)	A/I
Entitled to special refunds on medicines (ESRM), as % of aged 16-24 (231)	A/I
Entitled to special refunds on medicines (ESRM), as % of aged 25-39 (1809)	A/I
Entitled to special refunds on medicines (ESRM), as % of aged 40-64 (1810)	A/I
ESRM for psychosis, as % of aged 65 and over (408)	A/I
ESRM for diabetes, as % of aged 65 and over (1803)	A/I
ESRM for asthma, as % of aged 65 and over (1808)	A/I
ESRM for coronary heart disease, as % of aged 65 and over (1822)	A/I
ESRM for hypertension, as % of aged 65 and over (1821)	A/I
Service housing with 24-hour assistance, as % of aged 65 and over (1252)	D
Support for informal care: clients, as % of aged 75 and over (3262)	D
Living at home, as % of aged 75 and over (1570)	D
Household dwelling-units with one person, as % of aged 75 and over (2451)	R
Reimbursement for visits to private physicians, recipients as % of tot. pop. (692)	D
Visits in private dental care per 1000 inhabitants (3217)	D
Mortality among population aged 65 and over, as % of persons of same age (322)	D

Table 5: Variables used to estimate the static factor: Quality measures

Inputs (per 10 000 inhabitants)	Form
Dental assistants in primary health care (2623)	C/I
Dental hygienists in primary health care (2622)	C/I
Dentists in primary health care (2621)	C/I
Practical nurses in specialised health care (2644)	C/I
Practical nurses in primary health care (2638)	C/I
Physicians in primary health care (2635)	C/I
Assistant nurses in primary health care (2639)	C/I
Nurses in primary health care (2636)	C/I
Public health nurses in primary health care (2637)	C/I
Ward sisters in primary health care (3306)	C/I
Physiotherapists in primary health care (3307)	C/I
Radiographers in primary health care (3308)	C/I
Medical laboratory technologists in primary health care (3309)	C/I

Table 6: Variables used to estimate the static factor: Inputs & Coverage

B Appendix: results

Tables 8–11 present results for Model (1b).

Tables 9–11 present the highest factor loadings for PCs 2–4.

Controls	Form
Morbidity index, age standardised (184)	-
Long-term unemployed, as % of unemployed population (326)	R
Unemployment rate, as % of labour force (181)	R
Offenses against life and health recorded by the police, as % of tot. pop. (3113)	R
Social assistance, recipient persons during year, as % of tot. pop. (493)	R
Support in community care: a child welfare intervention, as % of aged 0-17 (1245)	R
Children aged 1-6 in municipally funded day care, as % of aged 1-6 (2955)	D
Population aged 0-14 as % of total population (1064)	DC
Population aged 15-64 as % of total population (1067)	DC
Population aged 65 and over as % of total population (1068)	DC
Loans, euros per capita (3180)	BC
Tax revenue, euros per capita (3177)	BC
Costs	
Net expenditure of the municipal health sector, euros per capita (1291)	-
Net expenditure on primary health care (including dental care), euros p.c. (1072)	-
Wage cost data (Source: Statistics Finland)	-
The price index of public expenditure (Source: Statistics Finland)	

Table 7: Control and cost variables

Component	Model (1b) Proportion, %	Cumulative prop., %
*pc*1	20.2	20.2
*pc*2	10.9	31.1
*pc*3	6.8	37.9
*pc*4	5.6	43.5
*pc*5	4.3	47.8
*pc*6	3.2	51.0
*pc*7	2.9	53.9
*pc*8	2.8	56.7

Table 8: Principal component analysis for Model (1b), N=1595

Model (1b) Variable	Factor loading
Nurses in primary health care	0.362
Assistant nurses in primary health care	0.331
Practical nurses in primary health care	0.326
Public health nurses in primary health care	0.303
Dental assistants in primary health care	0.284
Physiotherapists in primary health care	0.278
Ward sisters in primary health care	0.276
Physicians in primary health care	0.272
Radiographers in primary health care	0.241
Dentists in primary health care	0.236
Medical laboratory technologists in primary health care	0.227
Dental hygienists in primary health care	0.152
ESRM for diabetes, as % of aged 65 and over	0.083

Table 9: Estimation results for Model (1b), second component

Model (1b) Variable	Factor loading
Offenses against life and health recorded by the police	0.367
Social assistance, recipient persons as % of total population	0.269
Population aged 15-64 as % of total population	0.263
Support in community care as part of a child welfare intervention	0.258
Household dwelling-units with one person, as % of aged 75 and over	0.246
Psychiatric inpatient care, care days per 1000 inhabitants	0.236
Tax revenue, euros per capita	0.232
Outpatient visits in specialised health care per 1000 inhabitants	0.194
Diseases related to substance abuse: periods of care, as % of aged 15-24	0.176
Unemployment rate	0.155
Population aged 0-14 as % of total population	-0.204
Dental care patients in health centres per 1000 inhabitants	-0.262
Dentist visits in health centres per 1000 inhabitants	-0.323

Table 10: Estimation results for Model (1b), third component

Model (1b) Variable	Factor loading
Population aged 0-14 as % of total population	0.392
ESRM: asthma, as % of aged 65 and over	0.272
ESRM: coronary heart disease, as % of aged 65 and over	0.230
Support for informal care: clients, as % of aged 75 and over	0.225
Loans, euros per capita	0.221
ESRM: hypertension, as % of aged 65 and over	0.209
ESRM: diabetes, as % of aged 65 and over	0.206
Mortality among population aged 65 and over, as % of persons of same age	-0.154
Outpatient physician visits in primary health care per 1000 inhabitants	-0.180
Patients seen by a physician in primary health care as % of tot. pop.	-0.184
Household dwelling-units with one person, as % of aged 75 and over	-0.186
Inpatient primary health care, care days per 1000 inhabitants	-0.202
Population aged 65 and over as % of total population	-0.345

Table 11: Estimation results for Model (1b), fourth component

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GOVERNMENT INSTITUTE FOR ECONOMIC RESEARCH

Valtion taloudellinen tutkimuskeskus
Government Institute for Economic Research
P.O.Box 1279
FI-00101 Helsinki
Finland

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