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Developing robust composite measures of healthcare quality - Ranking intervals and dominance relations for Scottish Health Boards

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1 **ABSTRACT**

Although composite indicators are widely used to inform health system performance comparisons, such measures typically embed contentious assumptions, for instance about the weights assigned to constituent indicators. Moreover, although many comparative measures are constructed as ratios, the choice of denominator is not always straightforward. The conventional approach is to determine a single set of weights and to choose a single denominator, even though this involves considerable methodological difficulties.

9 This study proposes an alternative approach to handle incomplete information about an 10 appropriate set of weights and about a defensible denominator in composite indicators 11 which considers all feasible weights and can incorporate multiple denominators. We 12 illustrate this approach for comparative quality assessments of Scottish Health Boards. The 13 results (displayed as ranking intervals and dominance relations) help identify Boards 14 which cannot be ranked, say, worse than 4th or better than 7th.

Such rankings give policy-makers a sense of the uncertainty around ranks, indicating the extent to which action is warranted. By identifying the full range of rankings that the organizations under comparison may attain, the approach proposed here acknowledges imperfect information about the "correct" set of weights and the appropriate denominator and may thus help to increase transparency of and confidence in health system performance comparisons.

Key words: performance comparison; composite indicator; weight; denominator; ranking
interval; dominance relation.

23 **1** Introduction

The increasing complexity of health systems and the multidimensionality of health system 24 performance have reinforced calls for the production of composite measures of 25 performance (WHO, 2000, Healthcare Commission, 2005, Carinci et al., 2015). 26 Summarizing the information contained in diverse indicators in a single index and ranking 27 organisations or countries on that basis has the potential to present the "big picture", by 28 highlighting in a unified way to what extent the objectives of health systems related to 29 health outcomes, treatment appropriateness, and other dimensions have been met. Thus, 30 composite measures may seem an attractive approach to strengthen accountability, 31 32 facilitate communication with the public, and focus improvement efforts on poorly performing organisations (Goddard and Jacobs, 2009). 33

34

However, composite indicators also have important disadvantages. In contrast to assessing 35 performance based on a range of separate indicators, rankings based on aggregate 36 measures may disguise the sources of poor performance and thus obscure the best focus 37 for remedial action (Smith, 2002). Composite indicators are also highly sensitive to 38 methodological choices, in particular to the weights attached to constituent indicators (see 39 e.g. Jacobs et al., 2005, Reeves et al., 2007, OECD, 2008). In their analysis of hospital 40 performance based on star ratings in the English NHS, Jacobs et al. (2005) show, for 41 instance, how subtle changes in the weighting system lead some hospitals to jump almost 42 half of the league table. However, the techniques by which weights are determined are not 43 straightforward. In addition, although many comparative quality measures are constructed 44 as ratios, it is not necessarily obvious which indicators should be employed as 45

denominators (Schlaud et al., 1998). In the context of low-birthweight survival rates,
Guillen et al. (2011) illustrate how the choice of population denominator results in
considerable variation depending on whether survival is reported relative to all births; live
births; or neonatal intensive care unit admissions.

50

These concerns are critical especially when rankings have serious consequences for the 51 52 rankees. For example, six of the Chief Executives of the twelve lowest ranked hospitals in England's star rating system (the so-called "dirty dozen") lost their jobs as a result (Bevan 53 and Hamblin, 2009). It has been argued that France and Spain's apparently high ranking in 54 55 the WHO's 2000 assessment of health systems substantially diminished pressure for reform in these countries (Navarro, 2000). In Medicare's Premier Hospital Quality 56 Incentive Demonstration, a pay-for-performance scheme based on a composite quality 57 score, hospitals below the ninth decile faced a 2% deduction in their Medicare payment 58 (CMS, 2009). With such high stakes, understanding whether ranks are robust to alternative 59 60 assumptions seems critical.

61

This study proposes an alternative approach to handle the lack of information about an appropriate set of weights and about a defensible denominator in composite indicators. We make two main contributions. First, we demonstrate the use of an approach to ranking organisations based on ranking intervals and dominance relations which accounts for the full set of feasible weights. This avoids the need to settle on a single, potentially controversial set of weights as it is required for instance in data envelopment analysis (DEA), in which weights are chosen such that each organisation appears in its best possible

light (Cherchye et al., 2007). Feasible weights are less restrictive and thus potentially better able to increase transparency and to acknowledge imperfect information about the "correct" set of weights. The ranking intervals obtained with this approach can be said to be robust in the sense that they reflect the full range of rankings that the organizations under comparison may attain when weights are selected from their respective feasible weight sets. Second, we address the problem of choice of denominator in ratio-based measures of performance.

76

77 2 Challenges in developing composite indicators of healthcare quality

A composite indicator is commonly expressed as an additive model based on a weighted
sum of a set of performance indicators

80
$$C_k = \sum_{j=1}^J w_j x_{jk},$$
 (1)

where *J* is the number of constituent indicators, w_i is the weight attached to indicator *j*, and x_{jk} the score on indicator *j* for organisation *k*. Composite measures of this form require choices about (i) the indicators included; (ii) the methods used to transform indicators (to achieve a common unit of measurement); (iii) the weights applied; (iv) any aggregation rules used; and (v) adjustments for environmental influences on performance. In addition (vi), although many quality indicators are reported as ratios, the choice of denominator is not always straightforward.

The focus of this study is on problems (iii) and (vi), how to handle incomplete information about weights and about the choice of denominator. Below we review the conceptual

background and problems with conventional strategies to address these challenges. In the
empirical application, we explain the approaches taken to problems (i), (ii), (iv) and (v).

92

2.1 Valuation of multiple healthcare quality measures

Healthcare performance is multidimensional. However, without a functioning market, there is no price mechanism for comparison. To aggregate heterogeneous indicators into a summary measure of performance, weights are required which - analogous to prices should represent the opportunity cost of achieving improvements on each individual measure by capturing the relative value attached to an extra unit of it (Smith, 2002).

98

In practice, arriving at explicit trade-offs between different healthcare quality measures – 99 100 and thus exact specifications of weights – is highly contentious. First, it is often unclear *whose* preferences should be elicited. Weights used often reflect a single set of preferences, 101 although the evidence suggests substantial heterogeneity in preferences between and 102 within groups of policy-makers, patients and the public (Smith, 2002, Decancq and Lugo, 103 2012). Making precise judgments about the relative value of sub-indicators to the 104 composite is typically both politically controversial and cognitively demanding, thus 105 106 triggering reluctance among respondents to agree on a set of weights.

107

Second, there is no consensus on a single best method *how* to elicit weights. Different techniques for valuing health(care) outcomes – from simpler trade-off methods including ranking from most to least desired indicator and voting techniques to elaborate multi-

attribute approaches such as conjoint analysis and the analytic hierarchy process – tend to
produce different results. Each method has distinct advantages and disadvantages in terms
of feasibility, consistency and validity (Dolan, 1997, OECD, 2008, Appleby and Mulligan,
2000).

115

To circumvent perceived difficulties with normative approaches to set weights, data-driven 116 weighting systems are frequently used. For example, in data envelopment analysis (DEA) -117 a widespread method to compare organisations with multiple outputs and inputs 118 (Hollingsworth and Street, 2006) - weights are derived from the data so as to maximise 119 each organisation's performance (Cherchye et al., 2007). Each organisation receives a 120 different set of weights which casts it in the best possible light. However, data-driven 121 weights do not necessarily reflect meaningful trade-offs between performance domains 122 (Decancq and Lugo, 2012). There is no logical reason why an organisation values most 123 some performance domain because it performs relatively well on it: data-driven 124 approaches thus purport to solve a deep philosophical problem of how to derive values 125 from facts (Hume, 1739). 126

127

The conventional recommendation to address incomplete information about weights, and about the best method to elicit weights, is to conduct extensive sensitivity analysis on the chosen weights (Jacobs et al., 2005). However, traditional sensitivity analysis is problematic insofar as the choice of ranges of weights depends on the analyst. This form of sensitivity analysis thus corresponds to a "blind search" which is not explicitly oriented towards changes in ranks and the maximum and minimum plausible ranks an organisationcan attain.

135 **2.2 Choice of denominators**

Healthcare quality measures are often reported as ratio measures where a specific quality measure is divided by some measure of population. Not all comparative assessments of healthcare quality require a denominator. So-called "never events", events which are deemed to be entirely preventable, are reported as absolute numbers without reference to a denominator (NHS England, 2015). However, typically a ratio-based measure is used in order to make entities of different sizes comparable and to establish a common "currency unit" in which performance is assessed as "good" or "poor" relative to other organisations.

143

To construct ratio-based quality measures, the denominator should represent the best 144 available proxy for the population at risk (PAR) (Romano et al., 2010). However, the PAR of 145 experiencing a specific event is not always obvious. Suppose a national government wants 146 to assess performance on healthcare-associated infections (HAIs) among local health 147 authorities which are responsible for protecting the health of their local populations. To 148 149 measure health authority performance on HAIs, two measures of the PAR have been proposed: hospital occupied bed days (OBDs) and total population living in the health 150 authority area (Health Protection Scotland, 2007). 151

Using OBDs as the denominator implies that each day spent in the hospital puts patients at 153 risk of acquiring an infection there. However, OBDs ignore that some infections are not 154 acquired in hospital but in the community (Health Protection Scotland, 2014). Using OBDs 155 as the denominator might thus underestimate the actual number of exposed individuals. 156 Total population as a measure of the PAR, in contrast, implies the view that every person 157 could acquire an infection, independent of hospital activity (Health Protection Scotland, 158 159 2007). Nevertheless, total population might overestimate the PAR by including individuals facing no or a negligible risk of experiencing the event (Marlow, 1995). 160

161

Ideally, one would specify a numerator that is unambiguously linked to one single denominator (McKibben et al., 2005); for example, by excluding community-acquired infections that are present on admission to hospital from the numerator. In practice, it is however often difficult to distinguish between infections that were present on admission and those acquired during a hospital stay (Naessens and Huschka, 2004, Zhan et al., 2007).

168 If the "correct" PAR is not obvious, then Guillen et al. (2011) recommend to consider 169 different denominators to acquire a more complete perspective on the outcome of interest. 170 To this end, one could produce multiple ratios between all reasonable numerator and 171 denominator combinations. However, manual comparisons of multiple performance ratios 172 quickly become unwieldy. In a situation with, say, four numerators and three 173 denominators, one would obtain 12 performance ratios for each entity under scrutiny.

174

176 **3 Methods**

3.1 Ranking intervals and dominance relations for all feasible

178 weights

We here examine the use of an alternative approach to handle incomplete information about appropriate weights and a defensible denominator. This approach consists in developing ranking intervals and dominance relations based on the full set of feasible weights. It is also able to handle different choices of denominator variables.

183

We use the ratio-based efficiency analysis (REA) technique (Salo and Punkka, 2011). Suppose there are *K* Decision-Making Units (DMUs – the entities to be evaluated) that have *N* different measures for the numerator of a ratio and *M* measures for the denominator of a ratio. The values of the *n*th numerator and the *m*th denominator of the *k*th DMU are $y_{nk} \ge 0$ and $x_{mk} \ge 0$, respectively. Thus, the possible performance ratios of the DMU *k* are y_{nk}/x_{mk} , where n = 1, ..., N and m = 1, ..., M.

190

191 REA enables the aggregation of different numerators and denominators in a summary 192 measure of performance. The relative importance of the *n*th numerator and the *m*th 193 denominator is captured by nonnegative weights u_n and v_m , respectively. The aggregated 194 performance ratio of DMU *k* is defined as

195
$$E_k(u,v) = \frac{\sum_n u_n y_{nk}}{\sum_m v_m x_{mk}}.$$
 (2)

196

To examine pairwise relations between DMUs, REA uses the concept of dominance: DMU kdominates DMU l if the performance ratio of DMU k is at least as high as that of DMU l for all feasible weights and there exist some weights for which its performance ratio is strictly higher. If a dominance relation exists between two DMUs, one can be confident that for any set of assumptions, one DMU outperforms the other. The dominance relation between DMUs k and l is determined by the pairwise performance ratio

$$D_{k,l}(u,v) = \frac{E_k(u,v)}{E_l(u,v)}.$$
(3)

204

203

The maximum and the minimum of $D_{k,l}(u, v)$ over all feasible weights provide upper and lower interval bounds on how well DMU k performs relative to DMU l. Thus, if the minimum of $D_{k,l}$ is greater than one, DMU k dominates DMU l.

208

The ranking interval indicates the best and worst performance rankings a DMU k can attain relative to other DMUs over all feasible weights. The best ranking is determined by the minimum number of other DMUs with a strictly higher performance ratio. For instance, the best ranking as third for a given DMU means that, no matter how the weights are selected, there are at least two other DMUs with a strictly higher performance ratio. If for some feasible weights the performance ratio of a DMU is higher than or equal to the ratio of any other DMU, then its best ranking will be one. The worst ranking is computed similarly.

216

217 REA-based results are computed using general programming methods such as linear 218 programming and mixed integer programming (Bertsimas & Tsitsiklis, 1997). The idea behind the use of these optimisation methods is to find, for each DMU, the highest
(respectively the lowest) ranking of that DMU for all feasible numerator and denominator
weights.

222

3.2 Method strengths and limitations

There are several innovative characteristics, and advantages, to this approach. First, the 224 aggregation of numerators and the denominators is achieved without fixing a single set of 225 226 weights for each DMU. The key innovation of REA is that one compares the relative magnitude of the performance ratios between DMUs for all feasible weights (rather than 227 applying only the most favourable weighting of variables to each organisation as in DEA 228 (Cherchye et al., 2007)). Although one can obtain ranking intervals with DEA (by applying 229 different sets of weight restrictions), these intervals still represent the highest possible 230 performance for each set of weight restrictions. REA by contrast produces robust 231 information about organizational performance in the sense that the resulting intervals 232 reflect the full range of rankings that DMUs may attain for all feasible (from most to least 233 advantageous) weights. 234

235

Second, REA calculates pairwise comparisons between DMUs rather than comparing each DMU to an efficiency frontier as in DEA or stochastic frontier analysis. This makes REA results more robust than frontier-based results, since the introduction or removal of an outlier DMU can substantially change the location of the efficiency frontier (Banker et al.,

- 1986). In contrast, already established pairwise dominance relations obtained from REA
 cannot change if a new DMU is added; and the end points of any DMU's ranking interval can
 shift towards lower performance by at most one ranking.
- 243

Third, because REA is based on pairwise comparisons, it requires a minimum of only two DMUs. In contrast, frontier-based methods require a larger number of DMUs to construct the frontier. For DEA, for instance, Banker et al. (1986) proposed the simple rule of thumb that the number of DMUs should be at least three times the number of variables. This is problematic because the number of indicators typically far outstrips the number of organisations.

250

Where the choice of denominator is straightforward, ratio-based analysis is not necessary. One can calculate individual performance rates for the respective indicators and aggregate them as a weighted sum as in equation (1). This is akin to evaluating the numerator of the performance ratio (2).

255

We here use ratio-based analysis in order to illustrate robustness to different choices of denominator while, which is an important innovation of REA, simultaneously varying the numerators weights. Ratio-based measures have limitations. In particular, the use of a ratio function does not account for structural differences (such as a higher share of fixed costs) between organisations. This assumption implies that, in evaluating organisational performance, one does for instance not "allow" an organisation a higher number of HAIs (in ratio terms, e.g. per 100,000 population) only because it is relatively small in size. However,

this assumption seems justified in contexts where health policy objectives include the principle of ensuring equal quality of care regardless of a person's place of residence and where structural differences have been compensated for (e.g. via the funding system, as outlined below) so as to ensure a level playing field across organisations.

267

Ratio measures may be preferred when there is primarily a concern with evaluation (examining which organisations perform better or worse) rather than explanation (examining why organisations achieve particular performance outcomes, as in regression analysis). This paper addresses the problem of comparative evaluation.

3.3 System context and data

Selection of indicators. We illustrate the robust ranking interval approach in the context 273 of comparative quality assessments of Scottish Health Boards. In Scotland, responsibility 274 for the allocation of resources is decentralized to 14 territorial Boards. The ultimate 275 objectives of these Boards are to protect and improve the health of their populations 276 through planning for and delivering health services (Scottish Government, 2014). To 277 construct a composite indicator of the quality of care provided by Boards, we confined 278 ourselves to indicators used in the HEAT target system. This existing performance 279 management system is used by the Scottish Government to assess Health Board 280 performance. All indicators used here (Table 1) come from the official performance 281 measurement system, but are not meant to represent an exhaustive set of health system 282 objectives. We use two data sets: 283

284

285	<u>Part I</u> : To examine robustness to choices of weights, we analyze six indicators from the
286	HEAT target system intended to measure Boards' relative degree of achievement in
287	ensuring appropriate treatment. This analysis uses an additive model akin to analyzing the
288	numerator of the performance ratio (equation 2) subject to uncertainty about weights.
289	Part II: To examine robustness to alternative choices of denominator alongside uncertainty
290	about numerator weights, we relate the number of two types of HAIs (MRSA/MSSA and
291	C.difficile infections) to OBDs and total population. This analysis relies on the more
292	complex ratio-based model in equation (2). We focus on HAIs because there is a good
293	justification for two alternative denominators (as set out in section 2.2). REA-based
294	analyses with two numerators and two denominators thus show the full strength of the
295	ratio-based approach.

Data transformation. To avoid mixing different units of measurement and to achieve scale
invariance, data were normalized to the [0;1] range by dividing each value by the maximum
value for a given indicator.

299

Environmental adjustment. The 14 Health Boards differ in terms of demographic, epidemiological and regional factors which are beyond their control but might influence observed performance. However, in Scotland, Health Boards are allocated resources based on a formula that takes account of variations in healthcare needs which arise from differences in age and sex composition, morbidity, life circumstances, and excess costs of delivering services in some (especially rural) regions which are deemed unavoidable (ISD

Scotland, 2010). Thus, Boards have already been compensated for structural differences so that they can ensure the same level of quality. We acknowledge that the risk adjustment provided by this formula is not perfect. However, following this argument, it is not unreasonable to assume that Boards are comparable with respect to the performance indicators analysed here.

311

Tables 1 and 2 about here

312 **3.4 Weight restrictions on quality measures**

An advantage of REA is its ability to address incomplete information about weight specifications by using the full set of feasible weights. This can be an attractive option when one assumes complete ignorance about the relative value of averting particular events. However, while an elicitation of cardinal preferences over "how much" worse a, say, MRSA infection is compared to, say, an emergency admission may not feasible (e.g. due to high cognitive demands) or desirable (e.g. due to biases introduced by specific elicitation methods), one may obtain statements about which events are ordinally worse than others.

Introducing plausible weight restrictions based on ordinal preferences can be useful because this recognises people's ability to provide limited preference information about the relative badness of particular events without imposing implausibly exact weights. Restrictions on weights can be used to prevent inconsistencies with accepted views on the relative importance of measures analysed (Allen et al., 1997, Pedraja-Chaparro et al., 1997).

326 Based on their own subjective assessment, the research team arrived at a set of ordinal weights through pairwise comparisons of any two quality measures, along the lines "If you 327 328 could avoid either an emergency admission to hospital or an MRSA infection, which event would you rather avoid". Corresponding to their relative badness, events were ranked as 329 follows (from worst=1 to least bad=6): 330 331 1. an MRSA/MSSA infection; 2. an emergency admission; 332 333 3. a C.difficile infection; 4. having to wait longer than 18 weeks from referral to treatment; 334

5. having to wait more than 4 hours in A&E (we assumed a condition where patients are
in mild to moderate discomfort);

337 6. a delayed discharge.

338

In flexible weighting systems, the composite score may be heavily influenced by a sub-339 340 indicator that is marginally important in the wider health system context (Goddard and Jacobs, 2009). To address this problem, for Part I we made the (illustrative but reasonable) 341 assumption that avoiding a particular event can at most have half of the overall value 342 attached to avoiding an event of each of the six quality measures. This resulted in the 343 following proportional weight restrictions: avoiding an event of the worst healthcare 344 quality measure cannot be more than ten times as valuable as avoiding an event of the least 345 bad quality measure (since with six indicators, a minimum weight of 1/10 means that one 346 quality measure can have at most half of the weight mass). 347

For part II, we made the (illustrative but reasonable) assumption that avoiding one C.difficile infection must be at least 1/4 as valuable as avoiding one MRSA/MSSA infection.

No weight restrictions for denominator variables were used. In efficiency analysis, denominator weights have a clear interpretation, as they indicate the substitutability of different types of inputs (labor, capital, intermediate inputs). In quality comparisons, denominators represent different populations at risk. However, denominator weights lack a clear interpretation as in efficiency analysis since it is hard to think about trade-offs between different populations at risk.

357

358 **4 Results**

4.1 Robustness to choices of weights: Unrestricted and restricted

360 ranking intervals for feasible weight sets

The ranking intervals (Figures 1-3) show the possible rankings that Boards can attain for different assumptions about weight sets. If one uses all feasible weights (Figure 1), then one obtains wide and overlapping ranking intervals spanning 9 to 14 ranks for a given Board. With ordinal weight restrictions, the width of ranking intervals decreases to 3 to 11 ranks (Figure 2). Thus, uncertainty about relative performance decreases as weight restrictions are applied.

367

However, the impact of weight restrictions on reductions in uncertainty differs across
Boards. For Boards *L* and *H*, ordinal weight restrictions narrow the ranking interval from

11 respectively 12 ranks (Figure 1) to 3 possible ranks (Figure 2), thus clarifying Board performance. In contrast, for Boards *N*, *E*, *M* and *A*, ranking intervals remain wider, because these Boards perform better on some indicators, but worse on others (Table 2). Hence, the remaining flexibility to set weights influences the ranks these Boards may attain. For 7 out of 14 Boards (*K*, *F*, *B*, *E*, *C*, *A*, *J*), the additional use of proportional weight restrictions (Figure 3) further decreases uncertainty about relative ranks.

376

The width of the ranking interval reflects the impact of changes in weights. A narrow interval suggests that a Board's performance is robust to alternative modelling assumptions. For example, Board L (Figure 2) is ranked 3rd or higher no matter which assumptions are used. The interval bounds show the impact of modelling assumptions on relative ranks. Thus, one can be confident that Board *F*, for example, cannot be ranked worse than 7th and not better than 3nd.

383

Figures 1 to 3 about here

4.2 Dominance relations and comparative scope for improvement

Based on pairwise comparisons, REA results can be displayed in a unified way as a dominance relation (Figure 4): insofar as Boards are more superordinate or "higher up", their relative performance is more robust to changes in the weights attached to the constituent indicators. Orkney (K), Shetland (L) and Western Isles (N) are top performers since they are not dominated by any other Board. Ayrshire and Arran (A), Fife (D), Greater Glasgow and Clyde (G), Lothian (J) and Tayside (M) are dominated by the other Boards.

391

392 There are two main reasons for this differentiated status. First, a Board's performance on the constituent indicators plays a role (Table 2). For instance, all three island Boards 393 perform better than the rest of Scotland on MRSA/MSSA infections, 4-hour A&E waiting 394 times and 18WRTT. Second, the ordinal weight restrictions used influence the dominance 395 relations. In this example, performance on MRSA/MSSA infections is weighted more highly 396 397 than performance on emergency admissions, which in turn receives a higher weight than performance on C.difficile, etc. Inspection of the underlying data (Table 2) suggests that the 398 five Boards at the bottom of the dominance graph perform worse on MRSA/MSSA 399 400 infections and emergency admissions. Nevertheless, their overall performance results from poor performance on several (up to four) indicators and thus not exclusively from the 401 weighting scheme. 402

403

In Table 3, the value in row i and column j represents the minimal proportional improvement which Board i needs to reach Board j (by decreasing its rates, since these are "lower is better" indicators). Thus, if a value on row i and column j is presented, Board j performs better than Board i with all feasible weights and thus dominates Board i. For instance, Board A needs to reduce its rates on all the indicators by 8% so as not to be dominated by Board B. Non-dominated Boards are identified by rows without any values (Boards K, L, and N).

411

Multiple values on the same row mean that a Board is dominated by several Boards andwould be situated on lower levels of the dominance graph. Looking horizontally, one can

414	see the improvements needed for the five worst performing Boards J, G, D, M, A to become
415	non-dominated by the better-performing Boards. Looking vertically, one can identify the
416	distance that differentiates each Board from the national leaders, Boards K, L and N.
417	Figure 4 about here
418	Table 3 about here
419	

420 **4.3 Ratio-based analysis: Robustness to choice of denominator**

Table 4 examines robustness to different choices of denominator and different numerator weights. Although seven Boards perform similarly for both denominators, the other seven Boards jump three to eight ranks up or down the ranking depending on whether total population or OBDs is used as the denominator (for C.difficile infections). For MRSA/MSSA, three Boards jump four or five ranks for different choices of denominator. Thus, the choice of denominator will make a difference to measured performance of these Boards on HAIs.

427

REA-based ranking intervals, which show composite performance on MRSA/MSSA and C.difficile relative to OBDs and population, reveal seven Boards (marked in bold in Table 4) with a ranking interval spanning seven or more ranks. This uncertainty in ranking reflects, first, sensitivity to choice of denominator (e.g. Borders jumps up four ranks when MRSA/MSSA and C.difficile are measured relative to total population). Second, this may show differences in performance on MRSA/MSSA as opposed to C.difficile (e.g. Forth Valley 434 is ranked 13th on the former but 2nd on the latter relative to OBDs).

435

Table 4 about here

436 437

438 **5 Discussion**

We have proposed a methodological approach to address two pervasive challenges which 439 make the use of composite measures for robust performance comparisons in healthcare 440 difficult: How should heterogeneous indicators be weighted to obtain an aggregate 441 measure of performance? How to handle incomplete information about the "correct" 442 denominator in ratio-based indicators? As Jacobs et al. (2005) note, two responses to the 443 uncertainty inherent in composite indicators would be to dismiss composite indicators 444 altogether and instead estimate relative performance separately for each objective (an 445 example of this is Hauck and Street's (2006) multivariate multilevel approach that requires 446 no aggregation and weighting of multiple objectives at all); or to invest considerable 447 resources into more sophisticated modelling, such as elaborate preference elicitation. 448

449

In a context where information is inevitably incomplete but policy-makers remain interested in an overall measure of health system performance (OECD, 2008), we have demonstrated how REA offers a third way that openly provides indications of the uncertainty inherent in the valuation of objectives and choices of denominators. The approach is essentially based on agnosticism: When there are multiple reasonable denominators which each highlight aspects of performance – such as that an organisation can deliver high quality in terms of few HAIs relative to hospitalised and/or general

457 populations – then analysts need not restrict themselves to a single denominator. Our 458 results reinforce the insight that healthcare quality may be best thought of as a collection of 459 possible rates depending on how the denominator is specified rather than as a single 460 "right" rate (Guillen et al., 2011). Ranking intervals based on multiple denominators thus 461 may enable a more complete account of performance.

462

Similarly, if we know that quality measures are heterogeneous but are ignorant of the best method to weight them, then methods to construct composite indicators need to capture that lack of knowledge. Sensitivity analysis on weights is not a new idea; prior work – especially in the multidimensional well-being literature – includes explicit use of ranges of weights (Zhou et al., 2010); computation of multiple weighting schemes (Osberg and Sharpe, 2002); and global sensitivity analysis (Saltelli et al., 2008).

469

The REA approach adds to this work in two ways. First, consideration of incomplete information is built into the structure of the model. Ranking intervals give policy-makers a sense of the uncertainty around ranks, indicating the extent to which action is warranted. Our results show that, when one assumes complete ignorance about the relative weights assigned to different indicators, then it is impossible to differentiate the performance of Scottish Health Boards (Figure 1). Thus, one cannot say which organisations perform better or worse. Regulatory action based on such rankings would clearly be premature.

477

478 However, once some reasonable ordinal and proportional weight restrictions are applied,
479 organizational performance appears more clarified. The choice of weight restrictions may

differ between groups of people: different individuals may come up with different 480 orderings or proportionate weights concerning the relative badness (or goodness) of 481 particular events. However, if weight restrictions can be established (e.g. based on existing 482 consensus or medical evidence of disease severity), then they may provide useful insights. 483 When an organisation consistently appears at the bottom (Board G) or at the top (Board L; 484 in Figure 2) whichever set of weights is used, this may strengthen the rationale for policy 485 486 intervention. It supports the notion that settling on a unique set of weights is not always necessary to inform well-founded judgments (Foster and Sen, 1997). 487

488

Second, ranking intervals and dominance relations appear to offer relatively intuitive ways 489 to synthesise key messages contained in disparate indicators. This may help to 490 communicate in a unified way the results of comparative assessments to policy-makers, 491 possibly addressing the limitations of frontier-based approaches such as DEA and 492 stochastic frontier analysis whose complexity has tended to limit their practical influence 493 outside academic circles (Hussey et al., 2009, Hollingsworth and Street, 2006). 494 Visualisation of uncertainty also mitigates the loss of transparency due to opaque 495 methodological choices made about the valuation of objectives (Hauck and Street, 2006). 496

497

498 REA-type analyses are likely to be particularly useful under conditions where:

(i) the audience are policy-makers and managers rather than academics (since
results such as being "30% below the efficiency frontier" may not be easily
accessible to non-technical audiences and REA requires no concept of an efficiency
frontier);

- (ii) there are concerns about rank reversals due to sensitivity to outliers and the
 introduction or removal of organisations (since pairwise comparisons make REA
 results relatively robust to these biases); and
- (iii) there are relatively few organisations (since a large number of organisations is
 not needed to construct an efficiency frontier). However, there are also no inherent
 limitations to applying REA to large datasets.
- 509
- 510
- 511

512 6 Implications for policy and research

The agnosticism implied in REA may come at a price of incomplete orderings (in the form 513 of wide and overlapping ranking intervals). Ranking intervals will become wider and more 514 overlapping the more performance indicators are used (compared to the number of 515 organisations) and, at the same time, the weaker the correlation between these indicators 516 (i.e. the less information good or poor performance on one indicator provides about 517 relative performance on other indicators). The number of indicators and the appropriate 518 degree of correlation will depend on the purpose of the analysis. Wide and overlapping 519 ranking intervals do not indicate that REA is not applicable. For policy-makers and 520 521 managers, a key strength of REA is that wide and overlapping intervals visualize in a transparent way the existing uncertainty. 522

523

524 Evidence of uncertainty reinforces the need to use the results as signals for further 525 analysis, rather than for definitive judgments. Since weakly correlated indicators will make

rankings more sensitive to different sets of weights (Foster et al., 2012), the careful use of
weight restrictions becomes particularly important. Weight restrictions will tend to clarify
the results and make explicit the impact of subjective choices about the relative value of
different quality indicators on performance rankings.

530

Dominance relations that are based on pairwise comparisons between Boards provide 531 532 comparative performance assessments one can be confident about. Since dominance relations indicate that some DMU k performs at least as well as some other DMU l for all 533 feasible weights and there exist some weights for which it performs strictly better, this 534 535 information could, for instance, be used for setting performance targets across all 536 indicators included in the analysis. Since improvements on some indicators may require less effort than others, indicator-specific improvements would also be informative. 537 However, this would require a different approach. Gouveia et al. (2015), for instance, 538 employ slack-variables (which define the variable-specific distance to the efficiency 539 540 frontier) to estimate the improvements required for a DMU to reach the best performing organisation. However, this approach does not indicate the improvements needed to reach 541 some specific, non-efficient DMU as it is possible with our approach. This is particularly 542 relevant for policy and management and a strength of our study, since the top performing 543 organisation may not always be the most meaningful (and practically feasible) benchmark 544 for worse performing organisations. In a collegiate rather than competitive environment, 545 such results could help organisations to learn from better performing (dominating) peers. 546

547

548 For a large number of organisations (and dominance relations), the clear presentation and

communication of results to decision-makers becomes even more important. To simplify the dominance graph, DMUs which perform similarly can be grouped together (as with DMUs *D* and *M* in Figure 4). A large number of dominance relations can also be visualized using a matrix (see Table 3) which shows both the dominance relations and the magnitude of dominance.

554

Finally, it is essential to re-emphasize the importance of the other methodological choices (listed in section 2) that must be made when constructing a composite indicator; in particular, the initial selection of indicators and risk adjustment for environmental (uncontrollable) determinants of performance. If important indicators are omitted or irrelevant variables are included, then performance evaluations will be meaningless (Smith, 1997). The choice of performance metrics therefore needs to reflect a country's definition of valued outcomes of the health service (Dowd et al., 2014).

562

Concerning risk adjustment, in Scotland the funding formula is designed to enable all NHS 563 Boards to produce equal levels of performance. Since this formula takes account of 564 differences in population and local characteristics (e.g. rurality), in this study we have 565 followed the argument that risk adjustment has been implemented via the funding system 566 567 (Jacobs et al., 2006). However, the degree to which this argument holds depends on the accuracy and comprehensiveness of the formula. While for our study the direction of any 568 potential bias is difficult to determine, it is possible that inadequate risk adjustment has 569 affected observed Board performance on the constituent indicators. 570

As Smith (2003) notes, formula funding is fraught with challenges, such as that performance criteria have proved hard to include in the formula. This means that poor quality of care which increases levels of morbidity might be 'rewarded' with higher levels of funding. As a result, the link between resource allocation and performance measurement remains complex and an important avenue for future research.

577

578 **REFERENCES**

579	Allen, R., Athanassopoulos, A., Dyson, R. G. & Thanassoulis, E. (1997). Weights restrictions and value
580	judgements in Data Envelopment Analysis: Evolution, development and future directions. Annals of
581	Operations Research, 73, 13-34.
582	Appleby, J. & Mulligan, J. (2000). How well is the NHS performing? A composite performance indicator based on
583	public consultation, London, The King's Fund.
584	Banker, R. D., Conrad, R. F. & Strauss, R. P. (1986). A Comparative Application of Data Envelopment Analysis
585	and Translog Methods - an Illustrative Study of Hospital Production. <i>Management Science</i> , 32, 30-44.
586	Bertsimas, D., & Tsitsiklis, J. N. (1997). Introduction to linear optimization (Vol. 6). Belmont, MA: Athena
587	Scientific.
588	Bevan, G. & Hamblin, R. (2009). Hitting and missing targets by ambulance services for emergency calls:
589	Effects of different systems of performance measurement within the UK. Journal of the Royal
590	Statistical Society. Series A, 172, 161-190.
591	Carinci, F., Van Gool, K., Mainz, J., Veillard, J., Pichora, E. C., Januel, J. M., et al. (2015). Towards actionable
592	international comparisons of health system performance: expert revision of the OECD framework
593	and quality indicators. International Journal for Quality in Health Care, 27, 137-146.
594	Cherchye, L., Moesen, W., Rogge, N. & Van Puyenbroeck, T. (2007). An introduction to 'benefit of the doubt'
595	composite indicators. Social Indicators Research, 82, 111-145.
596	CMS (2009). Centers for Medicare & Medicaid Services. Premier Hospital Quality Incentive Demonstration:
597	Fact sheet.
598	http://www.cms.hhs.gov/HospitalQualityInits/downloads/HospitalPremierFactSheet200907.pdf [9
599	May 2014].
600	Decancq, K. & Lugo, M. A. (2012). Weights in multidimensional indices of wellbeing: An overview.
601	Econometric Reviews, 32, 7-34.
602	Dolan, P. (1997). Valuing health states: A comparison of methods. <i>Journal of Health Economics</i> , 16, 617-617.
603	Dowd, B., Swenson, T., Kane, R., Parashuram, S. & Coulam, R. (2014). Can Data Envelopment Analysis Provide
604	A Scalar Index Of 'Value'? <i>Health Economics</i> , 23, 1465-1480.
605	Foster, J. & Sen, A. (1997). <i>On Economic Inequality</i> , Oxford, Oxford University Press.
606	Foster, J. E., Mcgillivray, M. & Seth, S. (2012). Composite Indices: Rank Robustness, Statistical Association, and
607	Redundancy. Econometric Reviews, 32, 35-56.
608	Goddard, M. & Jacobs, R. (2009). Using composite indicators to measure performance in health care. <i>In:</i> Smith,
609	P., Mossialos, E., Papanicolas, I. & Leatherman, S. (eds.) <i>Performance measurement for health system</i>
610	<i>improvement: experiences, challenges and prospects.</i> Cambridge: Cambridge University Press, pp. 339-
611	368.
612	Gouveia, M., Dias, L., Antunes, C., Mota, M., Duarate, E. & Tenreiro, E. (2015). An application of value-based
613	DEA to identify the best practices in primary health care. <i>OR Spectrum. DOI 10.1007/s00291-015-</i>
614	0407-x.
615	Guillen, Ú., Demauro, S., Ma, L., Zupancic, J., Wang, E., Gafni, A. & Kirpalani, H. (2011). Survival rates in
616	extremely low birthweight infants depend on the denominator: avoiding potential for bias by
617	specifying denominators. American Journal of Obstetrics and Gynecology, 205, 329.e1-329.e7.
618	Hauck, K. & Street, A. (2006). Performance assessment in the context of multiple objectives: a multivariate
619	multilevel analysis. Journal of Health Economics, 25, 1029-48.
620	Healthcare Commission (2005). 2005 Performance Ratings, London, Healthcare Commission.
621	Health Protection Scotland (2007). Annual report on the surveillance of Clostridium difficile associated
622	disease (CDAD) in Scotland, Glasgow, Health Protection Scotland.
623	Health Protection Scotland (2014). <i>Healthcare Associated Infection Annual Report 2013</i> , Glasgow, Health
624	Protection Scotland.
625	Hollingsworth, B. & Street, A. (2006). The market for efficiency analysis of health care organisations. <i>Health</i>
626	<i>Economics</i> , 15, 1055-1059.
627	Hume, D. (1739). A Treatise of Human Nature. London: John Noon.
628	Hussey, P. S., De Vries, H., Romley, J., Wang, M. C., Chen, S. S., Shekelle, P. G. & Mcglynn, E. A. (2009). A
629	systematic review of health care efficiency measures. <i>Health Services Research</i> , 44, 784-805.
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- ISD Scotland (2010). Resource allocation. <u>http://www.isdscotland.org/Health-Topics/Finance/Resource-</u>
 <u>Allocation-Formula/information.asp</u> [11 November 2014].
- Jacobs, R., Goddard, M. & Smith, P. (2005). How robust are hospital ranks based on composite performance
 measures? *Medical Care*, 43, 1177-84.
- Jacobs, R., Smith, P. & Street, A. (2006). *Measuring efficiency in health care: analytic techniques and health policy*, Cambridge University Press.
- Marlow, A. (1995). Potential years of life lost: what is the denominator? *Journal of Epidemiology & Community Health*, 49, 320-2.
- Mckibben, L., Horan, T., Tokars, J. I., Fowler, G., Cardo, D. M., Pearson, et al. (2005). Guidance on Public
 Reporting of Healthcare-Associated Infections: Recommendations of the Healthcare Infection Control
 Practices Advisory Committee. *American Journal of Infection Control*, 33, 217-226.
- Naessens, J. M. & Huschka, T. R. (2004). Distinguishing hospital complications of care from pre-existing
 conditions. *International Journal for Quality in Health Care*, 16, 127-135.
- 643 Navarro, V. (2000). Assessment of the world health report 2000. Lancet, 356, 1598-1601.
- 644 NHS England (2015). *Revised Never Events Policy and Framework*, London, NHS England.
- 645 OECD (2008). Handbook on Constructing Composite Indicators, Paris, OECD.
- 646 Osberg, L. & Sharpe, A. (2002). An index of economic well-being for selected OECD countries. *Review of* 647 *Income and Wealth*, 48, 291-316.
- Pedraja-Chaparro, F., Salinas-Jimenez, J. & Smith, P. (1997). On the Role of Weight Restrictions in Data
 Envelopment Analysis. *Journal of Productivity Analysis*, 8, 215-230.
- Reeves, D., Campbell, S. M., Adams, J., Shekelle, P. G., Kontopantelis, E. & Roland, M. O. (2007). Combining
 multiple indicators of clinical quality: an evaluation of different analytic approaches. *Medical Care*,
 45, 489-96.
- Romano, P., Hussey, P. & Ritley, D. (2010). Selecting Quality and Resource Use Measures: A Decision Guide for
 Community Quality Collaboratives, Rockville, Agency For Healthcare Research And Quality.
- Salo, A. & Punkka, A. (2011). Ranking intervals and dominance relations for ratio-based efficiency analysis.
 Management Science, 57, 200-214.
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., et al. (2008). *Global Sensitivity Analysis: The Primer*, Wiley E-book.
- Schlaud, M., Brenner, M. H., Hoopmann, M. & Schwartz, F. W. (1998). Approaches to the denominator in
 practice-based epidemiology: a critical overview. *Journal of Epidemiology & Community Health*, 52,
 13S-19S.
- 662 Scottish Government (2014). NHS Boards. <u>http://www.scotland.gov.uk/Topics/Health/NHS-</u>
 663 <u>Workforce/NHS-Boards</u> [14 May 2014].
- Smith, P. (1997). Model misspecification in data envelopment analysis. *Annals of Operations Research*, 73, 233-252.
- Smith, P. (2002). Developing composite indicators for assessing health system efficiency. *In:* SMITH, P. (ed.)
 Measuring up: improving health system performance in OECD countries. Paris: OECD, pp. 295-318.
- Smith, P. C. (2003). Formula funding of public services: An economic analysis. Oxford Review of Economic
 Policy, 19, 301-322.
- WHO (2000). *The world health report 2000 Health systems: improving performance,* Geneva, World Health
 Organization.
- Karan, C. L., Elixhauser, A., Friedman, B., Houchens, R. & Chiang, Y. P. (2007). Modifying DRG-PPS to include
 only diagnoses present on admission Financial implications and challenges. *Medical Care*, 45, 288291.
- Zhou, P., Ang, B. W. & Zhou, D. Q. (2010). Weighting and aggregation in composite indicator construction: A
 multiplicative optimization approach. *Social Indicators Research*, 96, 169-181.

TABLES AND FIGURES

Table 1 Variables and descriptive statistics

	Definition	Mean	SD	Min	Max
Data for part l	: robustness to choices of w	eights and don	ninance relatio	ons	
18WRTT ^a	Number of patient journeys from referral to treatment over 18 weeks (among patients seen) per 100,000 RTT patient journeys from referral to treatment (among patients seen)	7,361	3,475	2,209	15,123
4-hour A&E waiting ^a	Number of recorded A&E waits lasting over 4 hours per 100,000 A&E attendances	4,739	3,090	730	9,172
Emergency admissions ^a	Number of emergency admissions among +75 years per 100,000 population	2,887	424	2,239	3,646
MRSA/MSSA ^a	Number of MRSA/MSSA infections per 100,000 population	23	10	4	36
C.difficile ^a	Number of Clostridium difficile infections per 100,000 population	44	28	14	123
Delayed dischargesª	Number of bed days lost due to delayed discharges per 100,000 occupied bed days	29	18	6	69
Data for part l	ll: robustness to choices of d	enominator			
Quality indica	tors (numerator variables)				
C.difficile ^a	Number of Clostridium difficile infections	133	123	8	399
MRSA/MSSA ^a	Number of MRSA/MSSA infections	108	114	1	413
Population in	dicators (denominator varia	ibles)			
Total population ^b	 Resident population (mid-year estimates) 	475,232	318,214	113,880	1,214,587
OBD ^a	Number of occupied bed days	113,244	98,182	20,723	365,951

679 Sources: ^aHEAT target system; ^bNational Records of Scotland. All data are for 2012/13.

Table 2 Comparative performance of Boards on the constituent six quality indicators, based on rates as shown in Table 1, part I

		18WRTT	4-hour A&E waiting	Emergency admissions	MRSA/MSSA	C.difficile	Delayed discharges
Α	Ayrshire & Arran	8,691	8,312	3,646	23	49	14
В	Borders	6,204	3,267	3,612	21	44	10
С	Dumfries & Galloway	6,170	5,987	3,130	27	36	29
D	Fife	6,899	4,559	2,725	35	26	69
Ε	Forth Valley	15,123	8,238	2,513	26	14	50
F	Grampian	9,343	3,812	2,239	25	24	43
G	Greater	8,523	6,956	3,061	34	33	17
	Glasgow & Clyde						
Н	Highland	5,817	2,199	2,825	17	24	45
I	Lanarkshire	5,551	8,667	2,671	24	35	24
J	Lothian	12,293	9,172	2,495	30	42	43
K	Orkney	2,649	1,663	2,661	9	84	6
L	Shetland	2,209	730	2,555	13	34	14
Μ	Tayside	8,701	1,119	2,964	36	50	21
Ν	Western	4,876	1,666	3,320	4	123	21
	Isles						

683

Table 3 Comparative scope for improvement needed to reach another target or

686 reference Board in Scotland

Dominated Board	Target or Reference Board														
		Α	В	C	D	Ε	F	G	Н	Ι	J	K	L	M	N
Ayrshire & Arran	A		8 %				2 %		25 %	2 %		22 %	36 %		2 %
Borders	В								9%			14%	27 %		
Dumfries & Galloway	С		<1 %				7 %		21 %			15 %	31 %		
Fife Forth Valley Grampian	D E F		3 %				11 % 7 %		24 % 12 % 6 %			17 % 3 %	32 % 21 % 15 %		
Greater Glasgow & Clyde	G		9%	8 %			16 %		29 %	11 %		22 %	36 %		2 %
Highland	Н												10 %		
Lanarkshire	Ι								12 %			6 %	23 %		
Lothian	J		4 %	2 %		6 %	18 %		23 %	11 %		18 %	33 %		
Orkney	Ŕ														
Shetland	L														
Tayside	Μ		8 %				4 %		20 %			25 %	36 %		
Western Isles	Ν														

Board	oard Per 100,000 OBDs		Per 100,00	Per 100,000 population				00,000 lation	Ranking interval for composite		
	Number of MRSA/MSSA	Rank	Number of MRSA/MSSA	Rank difference compared to OBDs	Number of C.difficile	Rank	Number of C.difficile	Rank difference compared to OBDs	performance on MRSA/MSSA and C.difficile relative to OBDs and population		
Shetland	21	3	13	0	55	1	34	-5	1-3		
Highland	87	4	17	0	124	6	24	+3	1-4		
Forth Valley	148	13	26	+4	78	2	14	+1	1-10		
Orkney	13	2	9	0	114	5	84	-8	2-13		
Western	4	1	4	ů 0	140	7	123	-7	2-14		
Isles	-	-	-	· ·		-					
Grampian	108	6	25	-2	105	3	24	+1	4-6		
Lanarkshire	113	8	24	+1	162	10	35	+3	5-8		
Borders	116	9	21	+4	241	14	44	+4	5-14		
Dumfries & Galloway	117	10	27	0	161	9	36	+1	6-10		
Greater Glasgow & Clyde	113	7	34	-5	109	4	33	-1	6-13		
Fife	211	14	35	+1	155	8	26	+4	6-14		
Ayrshire &	99	5	23	-1	211	13	49	+2	7-13		
Arran											
Lothian	127	11	30	0	177	11	42	+2	10-13		
Tayside	141	12	36	-2	195	12	50	0	12-14		
			P C								

689 Table 4 Performance on healthcare-associated infections relative to different choices of denominator

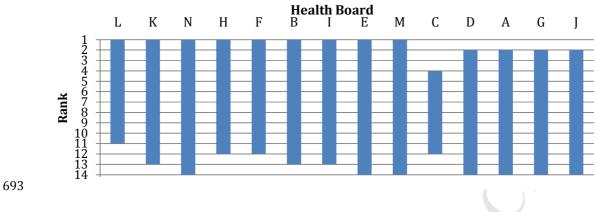
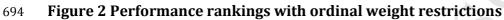
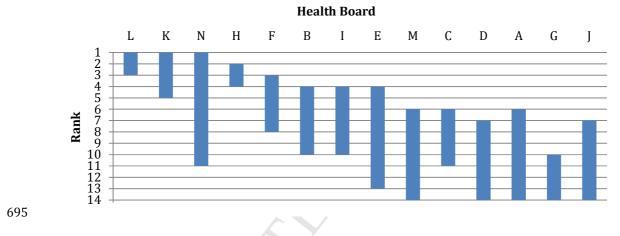
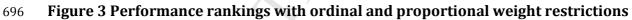
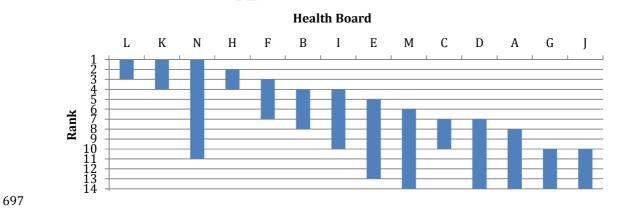


Figure 1 Performance rankings for all feasible weights



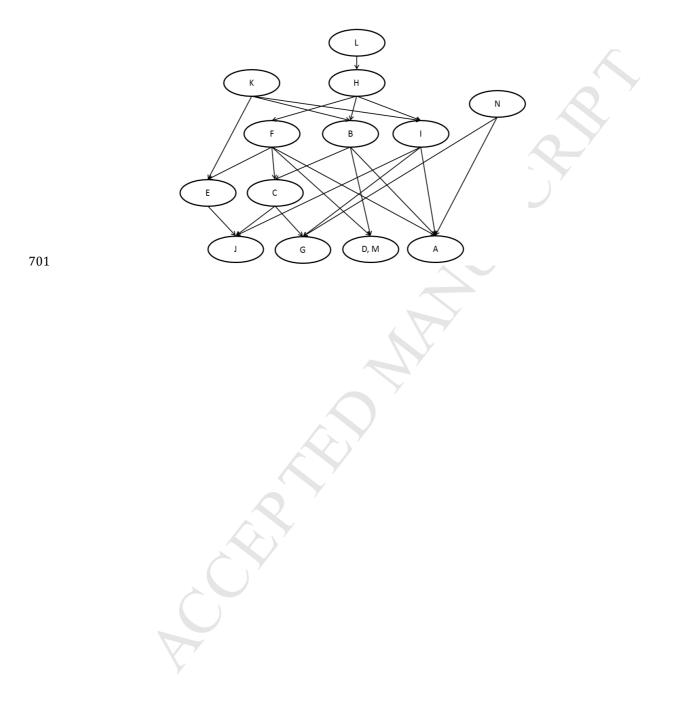






699 Figure 4 Dominance graph for Scottish Health Boards, based on ordinal and

700 proportional weight restrictions



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Research highlights

- Proposes a method to handle lack of information on weights and denominators in composite metrics
- Ranking intervals and dominance relations show performance rankings one can have confidence in
- Quality comparisons of Scottish Health Boards illustrate the impact of incomplete information