Aalto University
School of Business

A decision-analytic approach for supporting healthcare resource allocation

Eeva Vilkkumaa, Yrjänä Hynninen, and Ahti Salo
Aalto University School of Business, Department of Information and Service Economy
Aalti University School of Science, Department of Mathematics and Systems Analysis
Helsinki, Finland
IFORS 2017, July 21, Quebéc, Canada

Healthcare resources are limited

- There are limited resources for carrying out healthcare interventions:
  - Treatment actions
  - Diagnostic / prognostic tests to support treatment decisions
- It is important to allocate resources in a cost-effective way
  - Between patients
  - Between testing and treatment

Healthcare in Finland:

Population of 5.4 million

Universal coverage is accessible for all citizens & permanent residents

Healthcare expenditure is 9.4% (20 billion €) of GDP, out of which 75% (15 billion €) is publicly funded

Our contribution

- Typically, healthcare resource allocation is supported by cost-efficiency analysis (CEA) approaches, which
  - Convert health outcomes to monetary units
  - Compare only a few predetermined resource allocation strategies

- We develop a decision-analytic model in which
  - Testing and treatment strategies are optimized for multiple tests, testing stages, and treatment options
  - All Pareto optimal strategies are found

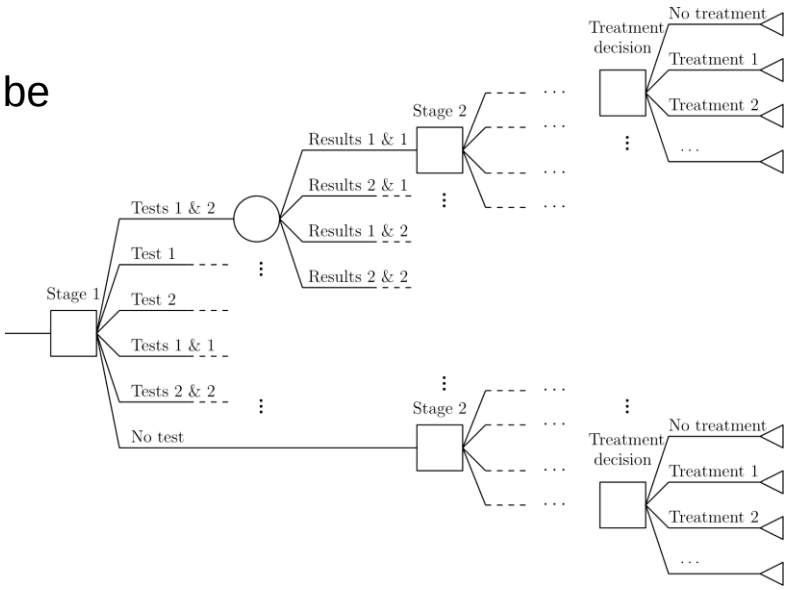
Model for testing and treatment strategies

- Patient's state of health is represented by a random variable $S \in \{0,1\}$, where $S = 1$ if the patient has a given disease
- Prior belief about the state of health is represented by initial probability $p(S = 1)$, referred to as prior risk
- The prior risk can be updated based on observed results of diagnostic tests carried out in K stages
  - The costs and accuracies of the tests are assumed to be known
- The updated risk after K testing stages is used to select a treatment action $a \in \{0, \dots, A\}$, where $a = 0$ represents no treatment
  - The direct and indirect costs and health outcomes of the actions conditioned on the true state of health are assumed to be known

Model for testing and treatment strategies

- Given prior risk $p(S = 1)$, a decision tree can be used to model decisions about
  - Which tests to carry out at each stage and
  - Which treatment action to ultimately select

- A testing and treatment strategy is a set of paths through this tree



- Each strategy is associated with expected cost *C* and expected health outcome *H*

Given the distribution of patient groups with different prior risks $p(S = 1)$ in the population, which strategy should be carried out to each group?

Utilitarianism vs. egalitarianism

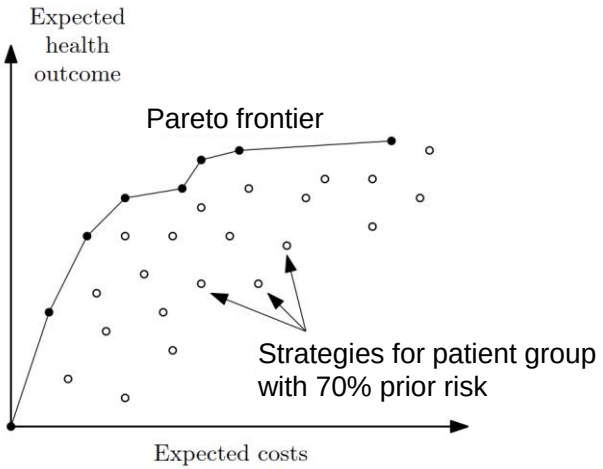
- The choice of strategies is made with respect to some population-level objective

- **Utilitarian approach:** maximize the total health outcome of a population
  - Dominant in standard economic evaluations of public healthcare interventions

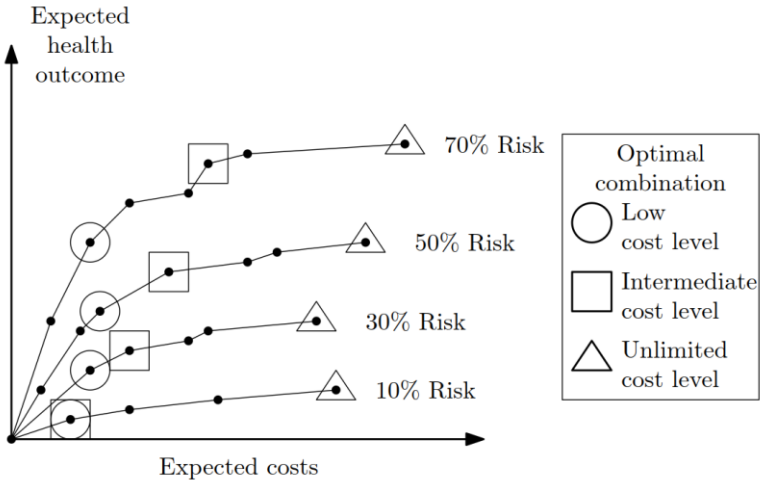
- **Egalitarian approach:** maximize the health outcome for those worst off
  - Considered more acceptable by the majority of people
  - Reduction of inequalities is the primary goal of many public healthcare interventions and programs

Two-phase optimization model to support resource allocation

- **Phase 1:** Identify Pareto optimal testing and treatment strategies for all patient groups corresponding to different levels of prior risk



- **Phase 2:** Select a combination of group-specific Pareto optimal strategies that maximizes the population-level objective (utilitarian or egalitarian) subject to an upper bound on the expected population-level cost



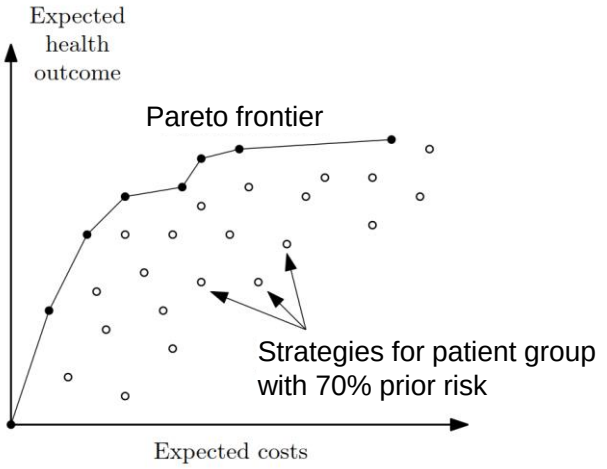
Phase 1: Identification of Pareto optimal strategies

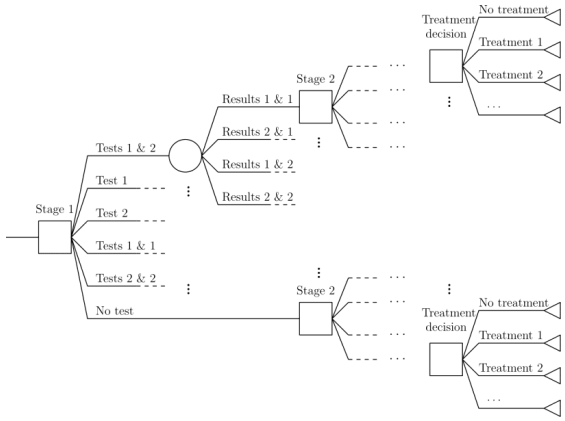
- The range [0,1] of prior risk $p(S = 1)$ is discretized into I points
  - E.g., $I = 101 \rightarrow p^i(S = 1) \in \{0\%, 1\%, \dots, 100\%\}$

- Given prior risk $p^i(S = 1)$, Pareto optimal strategies are solved by the ***ε*-constraint method**
  - Generate a sequence of upper bounds $b_1,\dots,b_J$ on the expected cost C such that $b_j = b_{j-1} + \varepsilon$
  - For each $j = 1, \dots, J$, find the strategy that maximizes the expected health outcome H subject to constraint $C \leq b_j$

- The J single-objective optimization problems corresponding to upper bounds $b_1,\dots,b_J$ are solved by a **dynamic programming algorithm** for each $p^i(S = 1), i = 1, \dots, I$

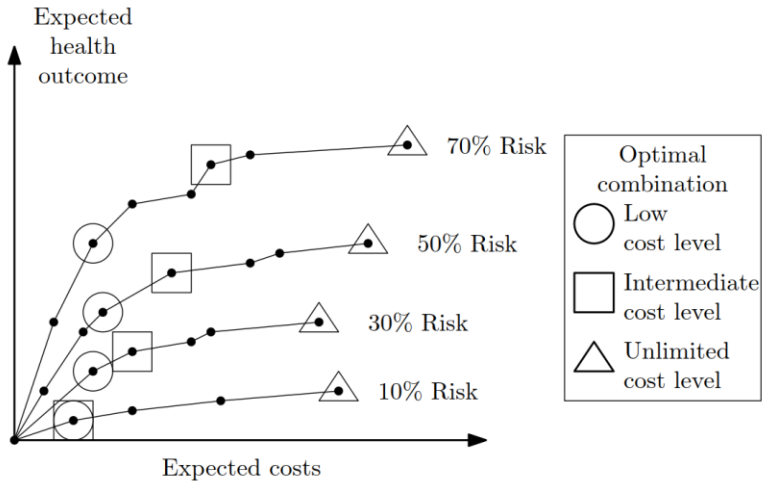
→ The $J_i \leq J$ unique optimal strategies $j_i \in \{1, \dots, J_i\}$ constitute the set of Pareto optimal strategies for patient group $i \in 1, \dots, I$





Phase 2: Optimizing the population-level strategy

- For all patient groups $i \in \{1, \dots, I\}$ and group-specific Pareto optimal strategies $j_i \in \{1, \dots, J_i\}$, we denote:
  - d_i : number of patients in group i with prior risk $p^i(S = 1)$
  - c_{i,j_i}: expected cost of Pareto optimal strategy j_i for patient group i
  - h_{i,j_i}: expected health outcome of Pareto optimal strategy j_i for patient group i
  - $x_{i,j_i} \in \{0,1\}$: decision variable such that $x_{i,j_i} = 1$ if and only if strategy j_i is carried out for patient group i



- B: upper bound on total expected population-level cost

Phase 2: Optimizing the population-level strategy

- **Utilitarian approach:**

$$U^* = \max_{\boldsymbol{x}} \sum_{i=1}^{I} \sum_{j_i=1}^{J_i} x_{i,j_i} d_i h_{i,j_i}$$

$$\text{subject to } \sum_{i=1}^{I} \sum_{j_i=1}^{J_i} x_{i,j_i} d_i c_{i,j_i} \leq B$$

$$\sum_{j=1}^{J_i} x_{i,j_i} = 1 \text{ for all } i$$

$$x_{i,j_i} \in \{0,1\} \text{ for all } i, j_i$$

Maximize the sum of expected health outcomes for all patient groups

The sum of expected group-specific costs cannot exceed the upper bound on the expected population-level cost

Exactly one strategy is selected for each group

Phase 2: Optimizing the population-level strategy

- **Egalitarian approach:**

$$E^* = \operatorname{lex}\max_{\boldsymbol{x}} f(\boldsymbol{x})$$

$$\text{subject to } \sum_{i=1}^{I}\sum_{j_i=1}^{J_i} x_{i,j_i} d_i c_{i,j_i} \leq B$$

$$\sum_{j=1}^{J_i} x_{i,j_i} = 1 \text{ for all } i$$

$$x_{i,j_i} \in \{0,1\} \text{ for all } i, j_i$$

The objective function is $f(\boldsymbol{x}) = [f_{i_1}(\boldsymbol{x}_{i_1}), \dots, f_{i_I}(\boldsymbol{x}_{i_I})]$, where

- $f_i(\boldsymbol{x}_i) = \sum_{j=1}^{J_i} x_{i,j_i} d_i h_{i,j_i}$ is the expected health outcome of patient group i and
- $f_{i_1}(\boldsymbol{x}_{i_1}) \leq \cdots \leq f_{i_I}(\boldsymbol{x}_{i_I})$ so that the expected health outcomes are arranged in increasing order

Case study: Prevention of CVD

- Cardiovascular diseases (CVDs) are a leading global cause of death

- The risk of a CVD event can be decreased by 25% through statin medication treatment
  - 10-year cost = 1,927€/patient

		Treatment	No treatment
Costs (€)	CVD event	12,177	14,415
	No event	1,927	0
Health outcomes (QALY)	CVD event	7.16	6.99
	No event	7.69	7.71

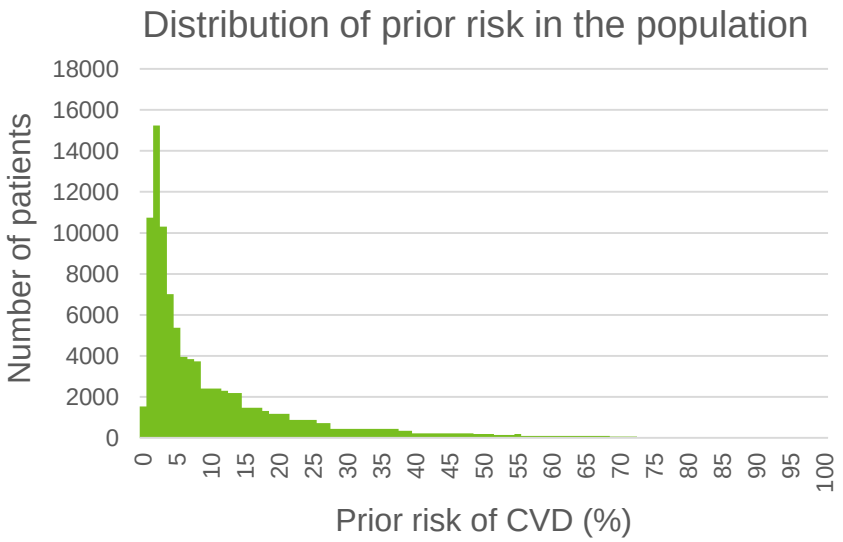
- Two prognostic tests to be used in two stages:
  - Framingham Risk Score (FRS): regression model on age, sex, cholesterol, systolic blood pressure, BMI, smoking, diabetes, medication, PR interval etc.
  - Genetic Risk Score (GRS): based on 49,310 single-nucleotide polymorphisms

	Cost (€)
FRS	173
GRS	200

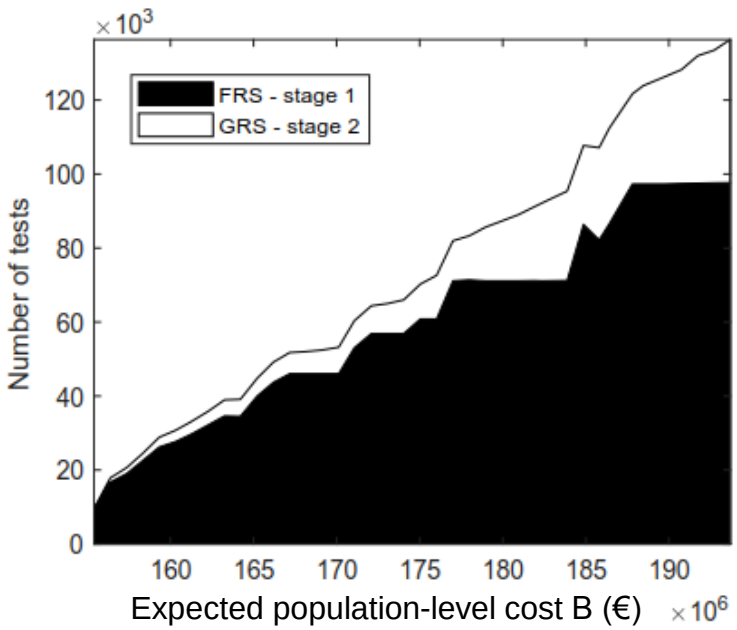
- Accuracies of FRS/GRS are obtained from FINRISK studies

Case study: Prevention of CVD

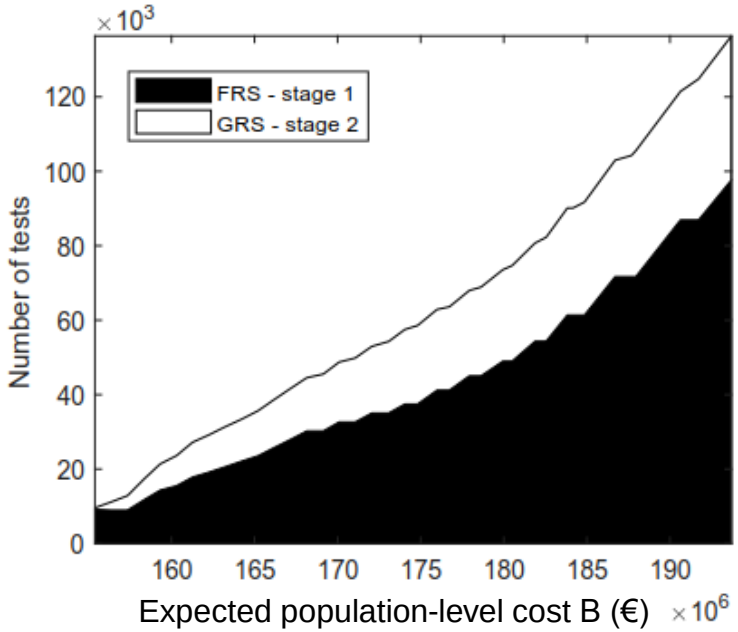
- Testing and treatment strategies are optimized for a population of 100,000 patients aged > 45
- Distribution d_i of patients with prior risk 0%,1%,…,100% in the population is based on FINRISK function applied to European Standard Population
- Population-level strategies are optimized for upper bounds $B \in \{155{,}156, \ldots, 194\}$ M€ on the population-level expected cost



Allocation of resources between tests



(a) Utilitarian strategy

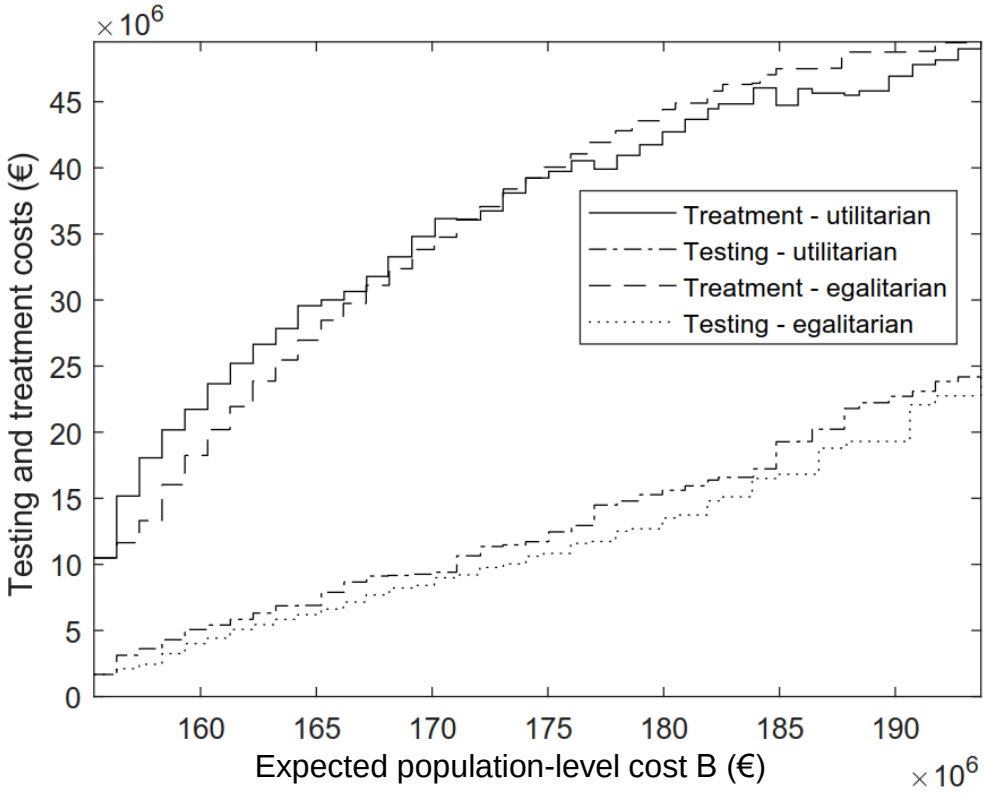


(b) Egalitarian strategy

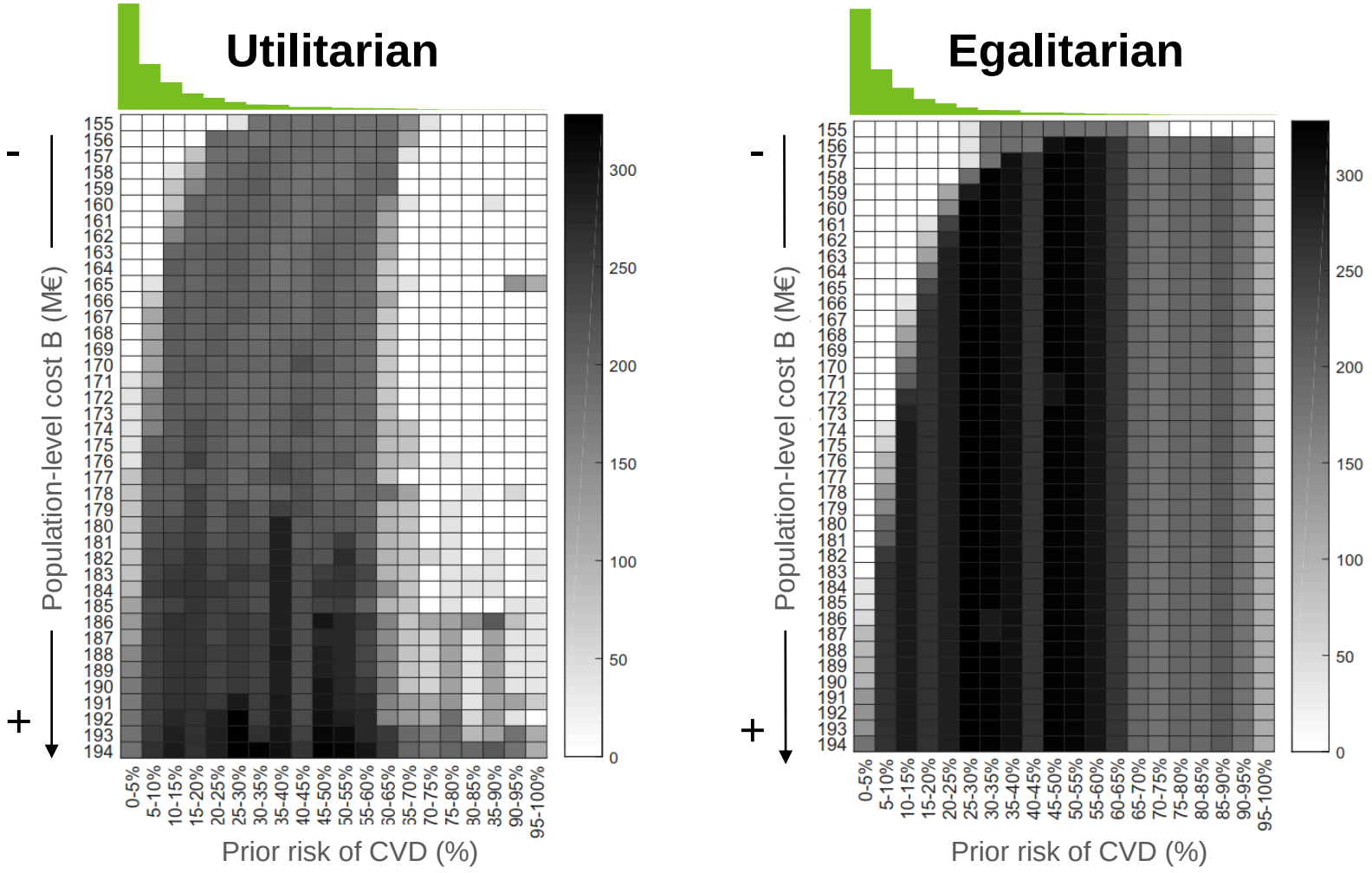
- Even at the lowest cost level 155M€, allocating some resources to testing is optimal
- The more expensive and accurate GRS is used more in the egalitarian approach

Allocation of resources between testing and treatment

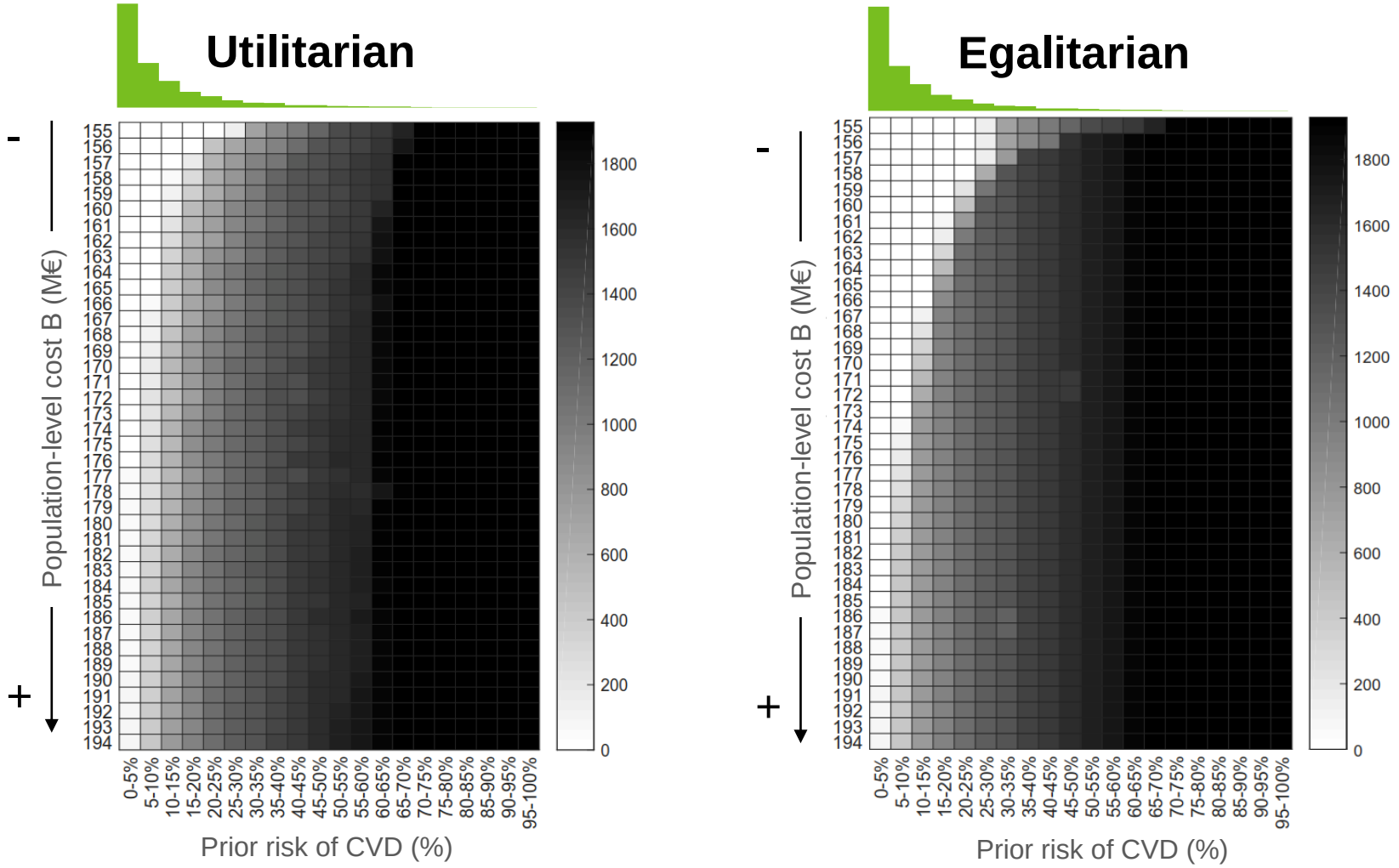
- The relative share of resources used on testing increases when the cost level increases



Allocation of testing resources between patient groups

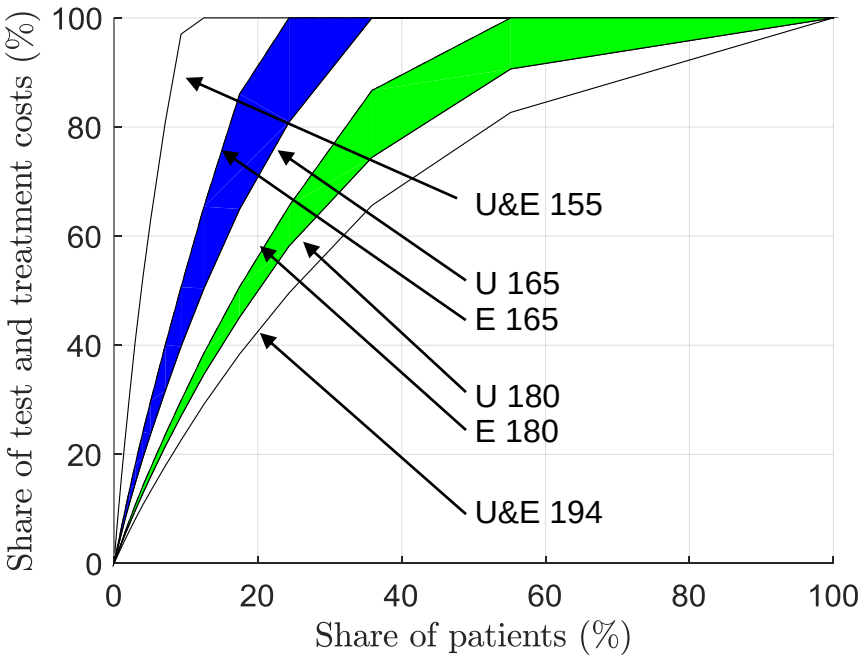


Allocation of treatment resources between patient groups



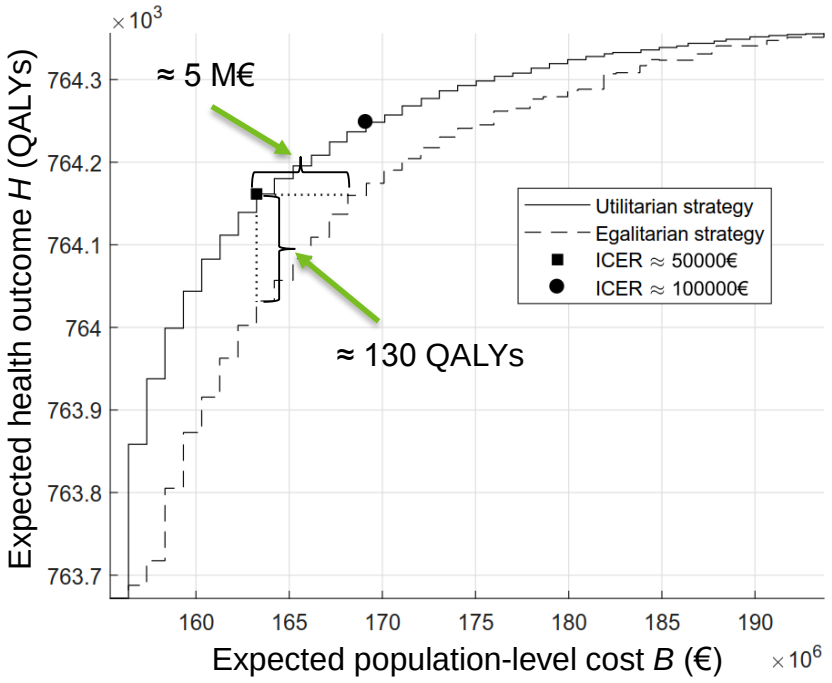
Allocation of testing and treatment resources between patient groups

- At minimum cost level 155 M€,
  - No difference between utilitarian & egalitarian
  - 12.5% of patients use all resources
- At low cost level 165 M€, all resources are used by
  - 24% of patients in the egalitarian approach
  - 36% of patients in the utilitarian approach
- At high cost level 180 M€,
  - 55% of patients use all resources in the egalitarian approach
  - 55% of patients use 91% of resources in the utilitarian approach
- At maximum cost level 194 M€,
  - No difference between utilitarian & egalitarian
  - Each patient can be tested and treated optimally



Cost-effectiveness and cost of equity

- Decisions about the appropriate cost level can be supported by plotting the expected population-level health outcome *H* as a function of cost level *B*
- The cost-effectiveness of different cost levels can be described by the incremental cost-effectiveness ratio (ICER)
  - Marginal cost of one QALY gained
  - Inverse of the derivative of the (*B*,*H*)-curve
- The cost of adopting an egalitarian approach can be measured by cost of equity:
  - Increase in expected cost level needed to maintain the expected health outcome
  - Decrease in expected health outcome required to maintain the expected cost level



Conclusions

- We developed a decision-analytic model to support healthcare resource allocation
  - Between testing and treatment
  - Between patient groups with different prior risk levels

- The model can be used to
  - Understand the impacts of choosing a utilitarian vs. egalitarian approach
  - Optimize the use of existing testing technologies and treatment options
  - Assess *ex ante* whether it pays off for the society to invest in a new testing technology / treatment option

Next steps

- Modeling of time dynamics (deterioration/improvement of health over time, changes in demographics, resulting changes in optimal resource allocation)
- Obtaining more precise estimates about prior risk and time dynamics through the use of individual patient data & predictive analytics
- Building multimorbidity models (e.g., CVD and type II diabetes)
- Development of robust decision recommendations through the use of incomplete probability information

Thank you!

Questions or comments?