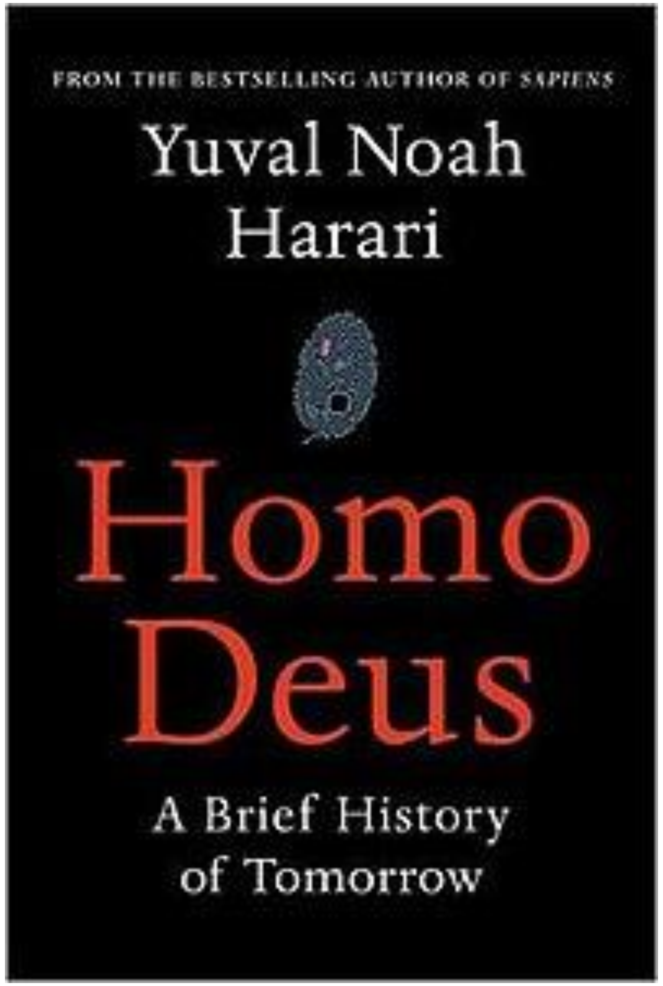
What can big data do for public health palliative care research?

Joachim Cohen

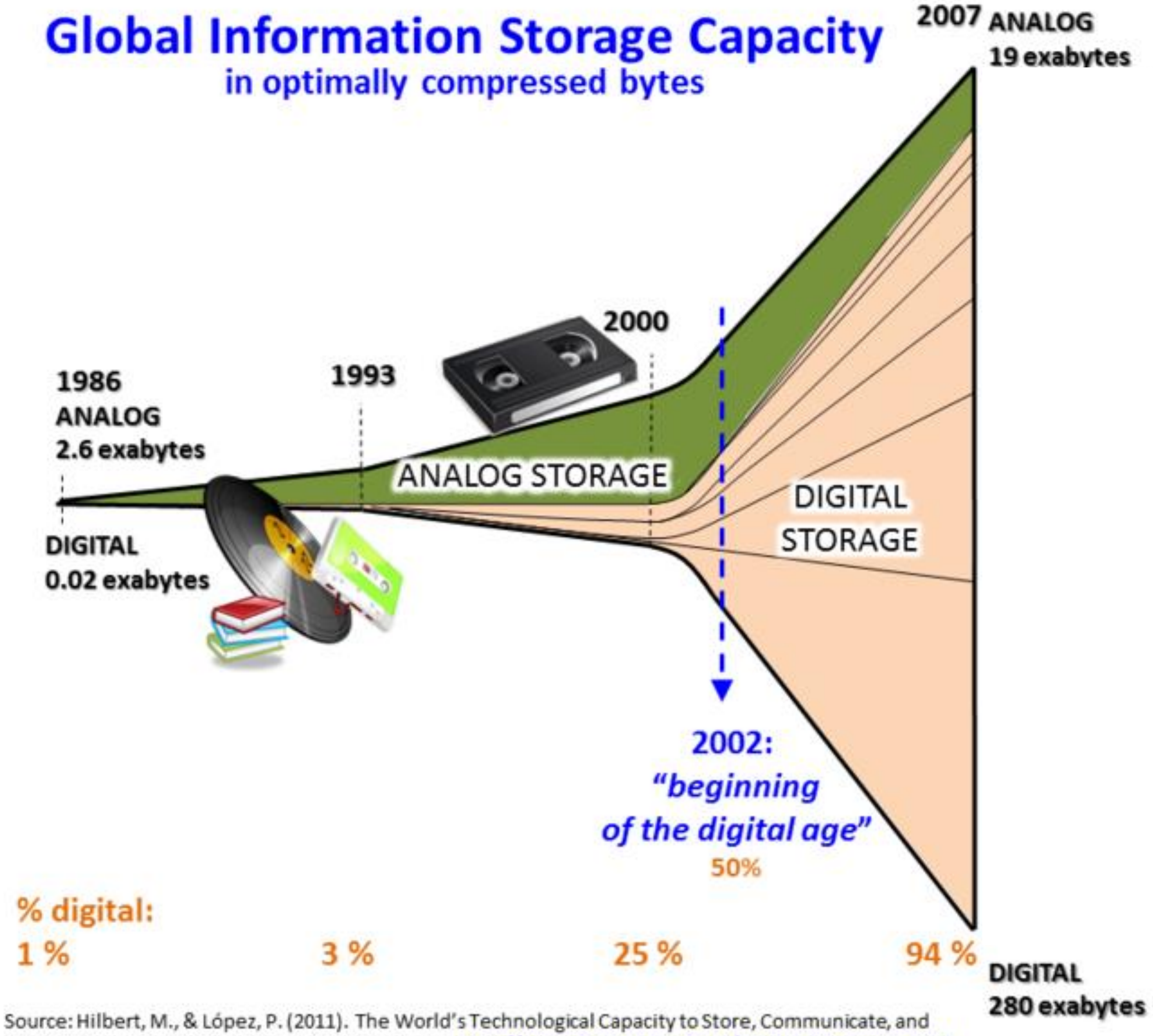
Big data as the promise for health care?

Cambridge Analytica

Big data as the promise for health care?



Big data as the promise for health care?



Source: Hilbert, M., & López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. *Science*, 332(6025), 60 –65. http://www.martinhilbert.net/WorldInfoCapacity.html

Big data as the promise for health care?

Assist in addressing various public health functions:

1. Population needs assessment and monitoring
2. Health care system & quality of care evaluations
3. Evaluation of policies, interventions, programs
4. Providing better evidence about effectiveness where this is difficult
5. More efficient RCTs
6. Algorithms for prediction and prospective decision support

What can big data do for end-of-life care?

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What big data?

Health care use

For every use:

- Nome
- date
- by wh
- cost,
- …

Medication dispensions:

For every dispension:

End-of-Life Care dataset

Cohort of deaths 2010-2015

For every death:

- Cause and place of death
- Cancer diagnosis
- All health care use last 24 months
- All medication use last 24 months
- Sociodemographics
- …

Cancer Registry

For every new diagnosis:

- Type (ICD-O)
- Date
- TNM
- …

ion data

resident:

aphic information

uation

Death certificate data

Census data

Housing information

Function 1: population needs assessment and monitoring

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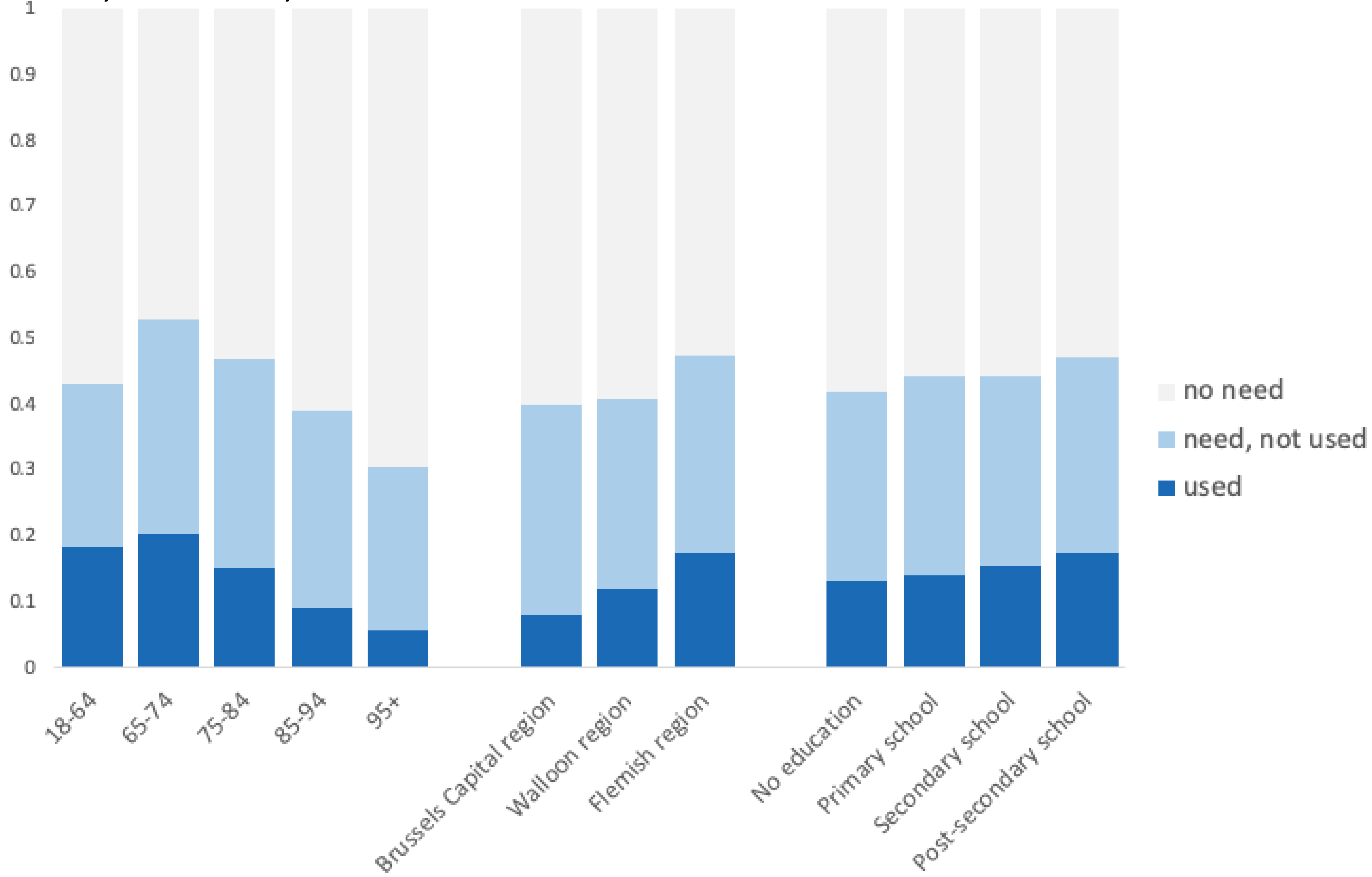
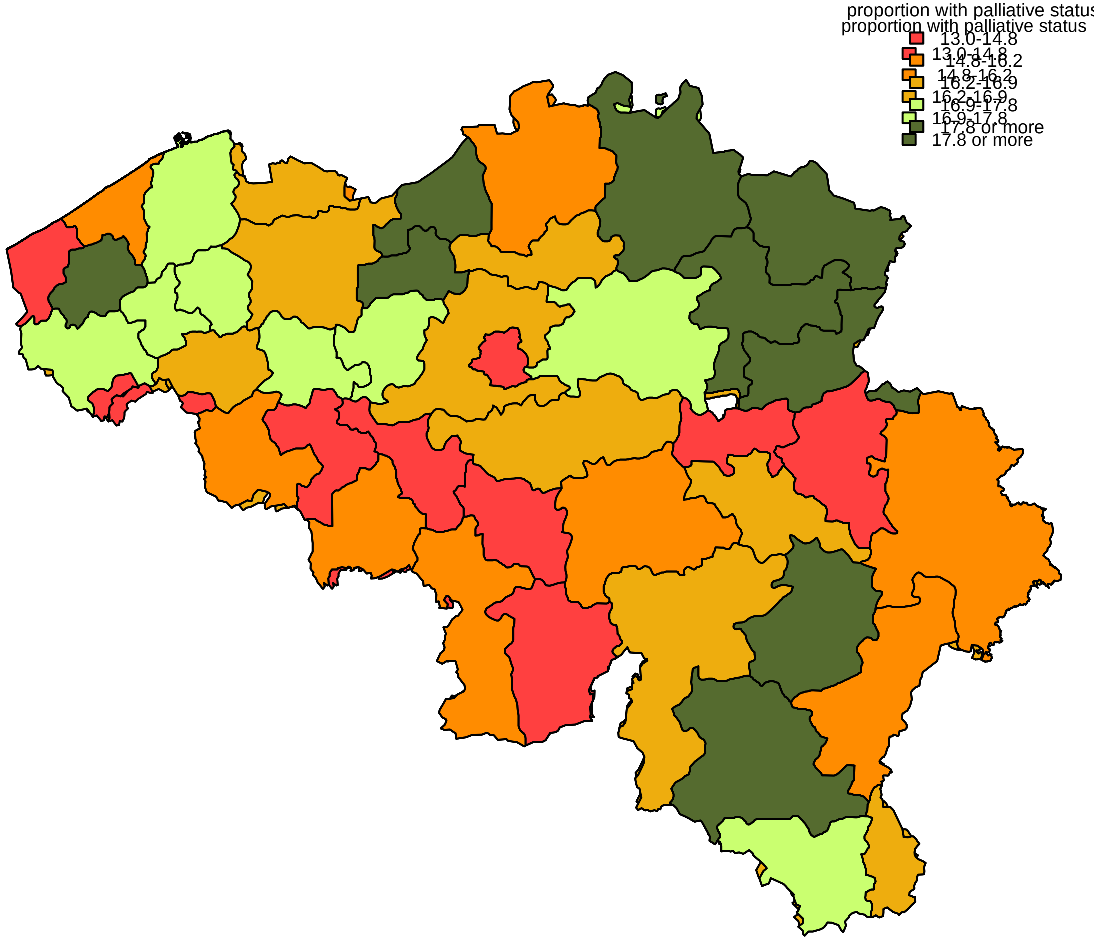
Proportion of home-dwelling population in need of PC actually using home PC differs by age and region, 2015, N= 87,007



Regional variation in receiving palliative home care



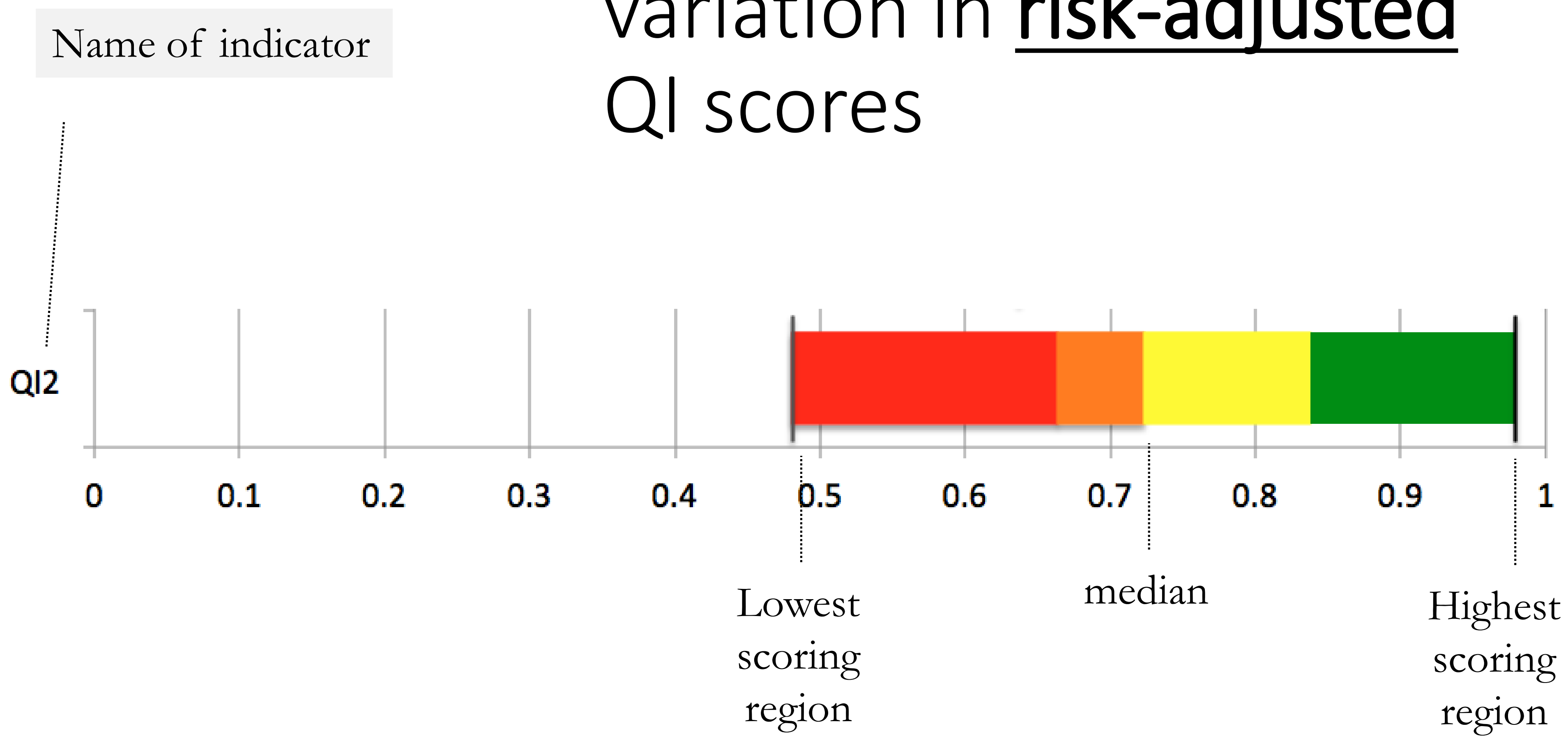
Adjusting for:

- Age
- Sex
- Diagnosis
- Household composition
- Income
- Educational level
- Urbanicity
- Care severity (hospitalizations in last 2 years
- Care dependency

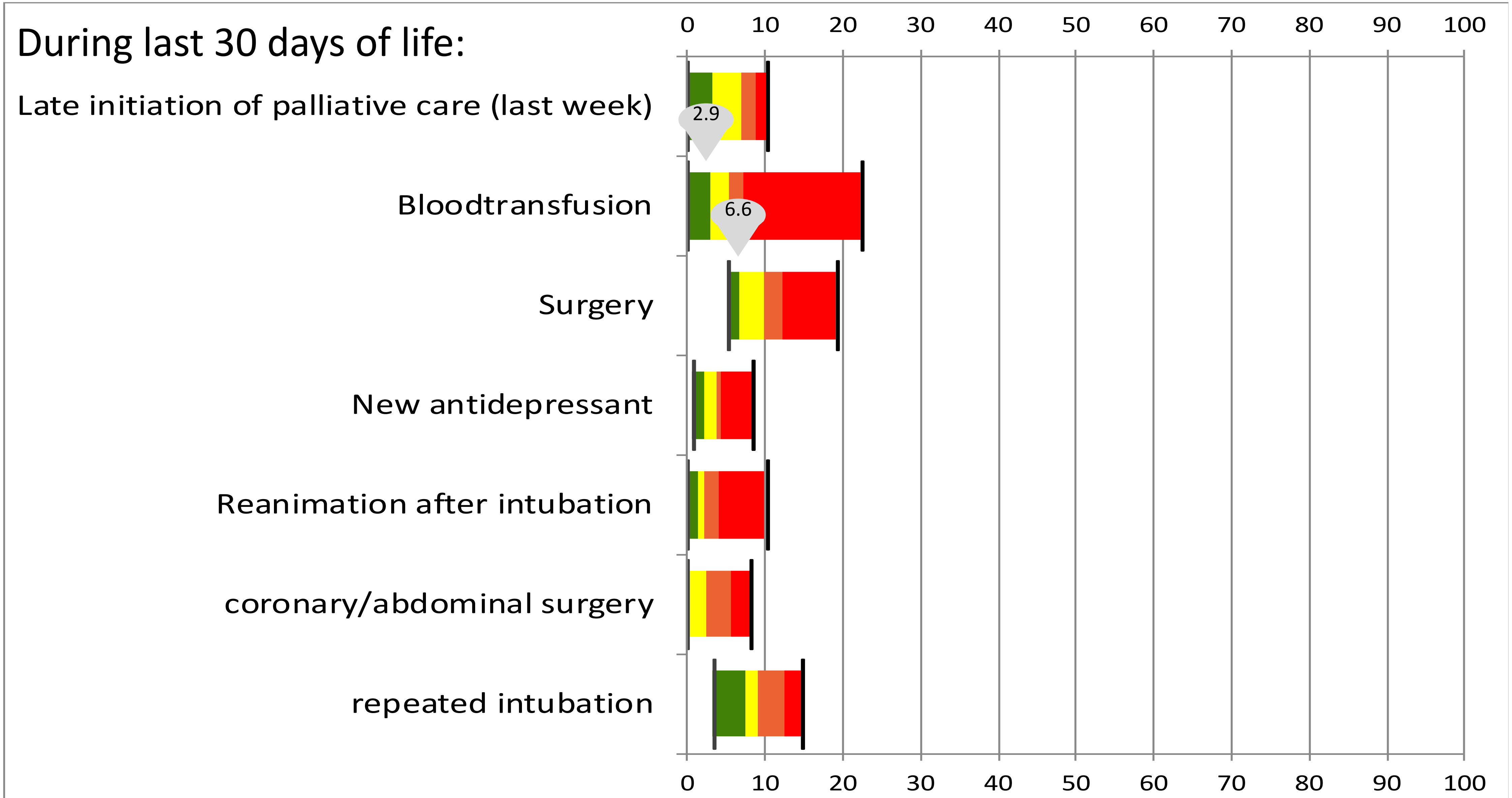
Function 2: Health care system & quality of care evaluations


Oostende
Brugge
Gent
Sint-Niklaas
Antwerpen
Turnhout
Mechelen
Roeselare
Kortrijk
Aalst
Brussel
Leuven
Hasselt
Genk

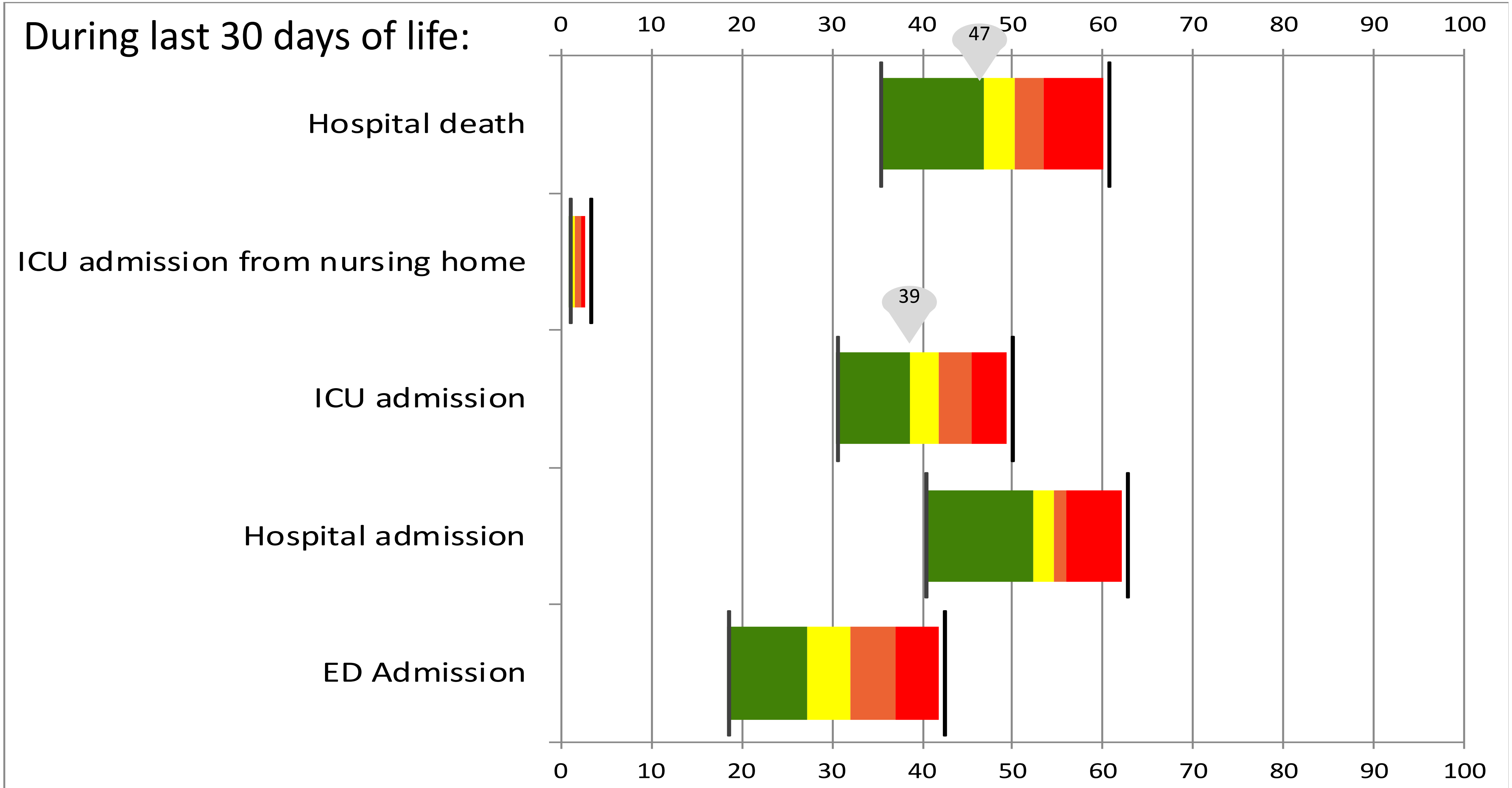
How to read the region-variation in **risk-adjusted** QI scores



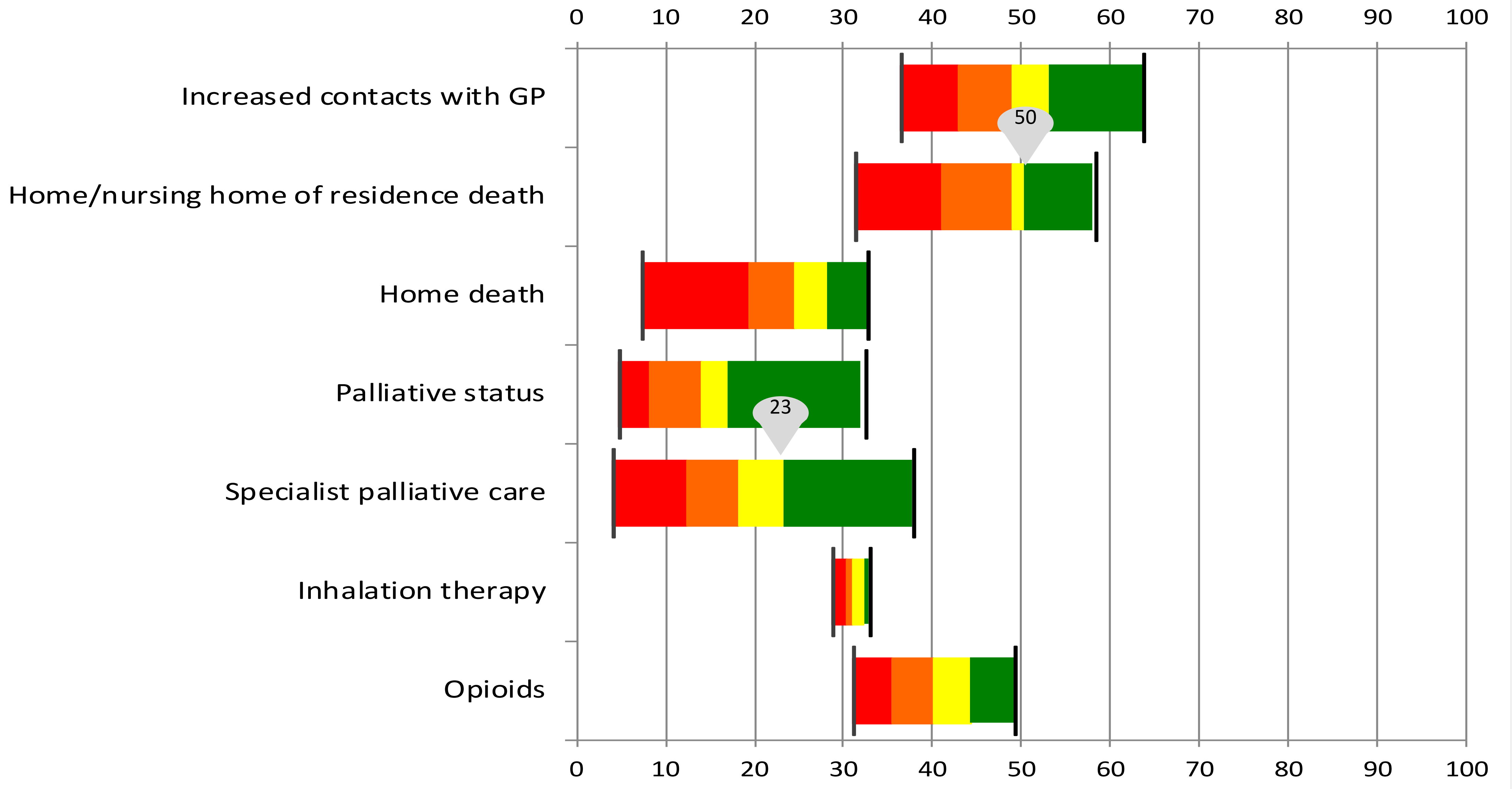
Strong variation between regions in inappropriate EOLC for those with COPD, n= 4,231



Strong variation between regions in inappropriate EOLC for those with COPD, n= 4,231



Strong variation between regions in **appropriate** EOLC for those with COPD, n= 4,231

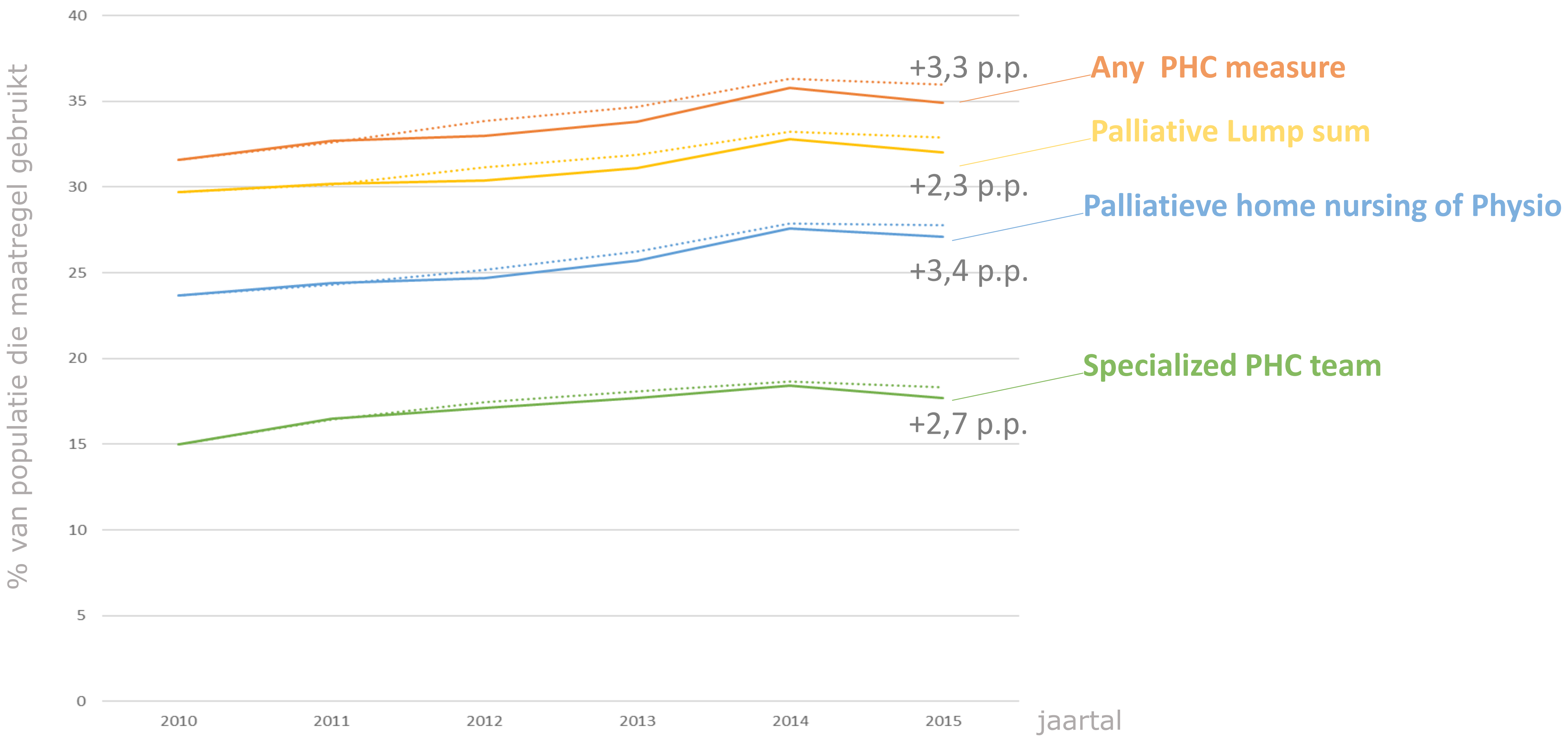


Function 3: Evaluation of policies, interventions, programs

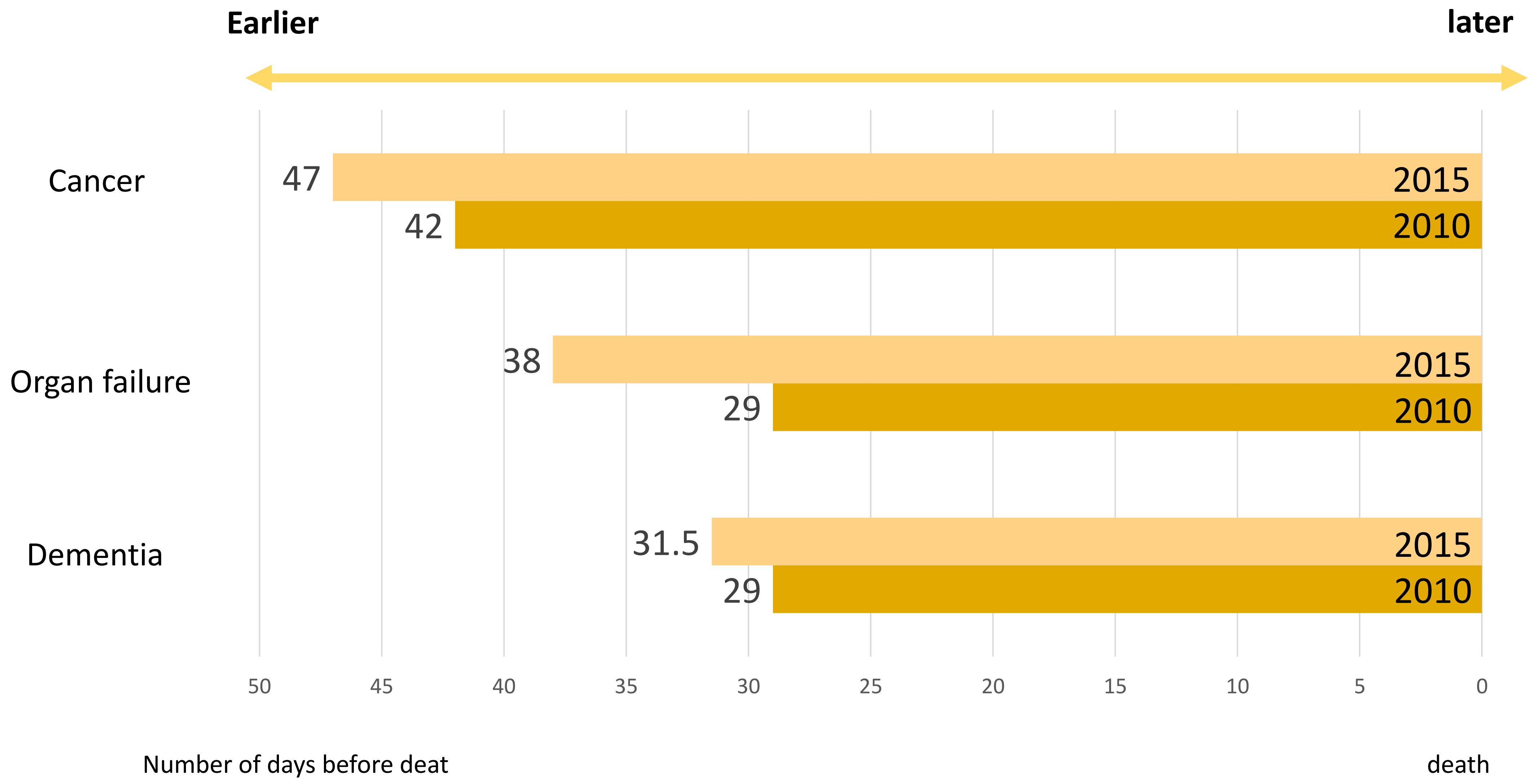
Time trends to evaluate whether policies have intended effects

- Use of palliative care
- timing of palliative care

Increase in use of palliative home care (PHC) measures 2010-2015



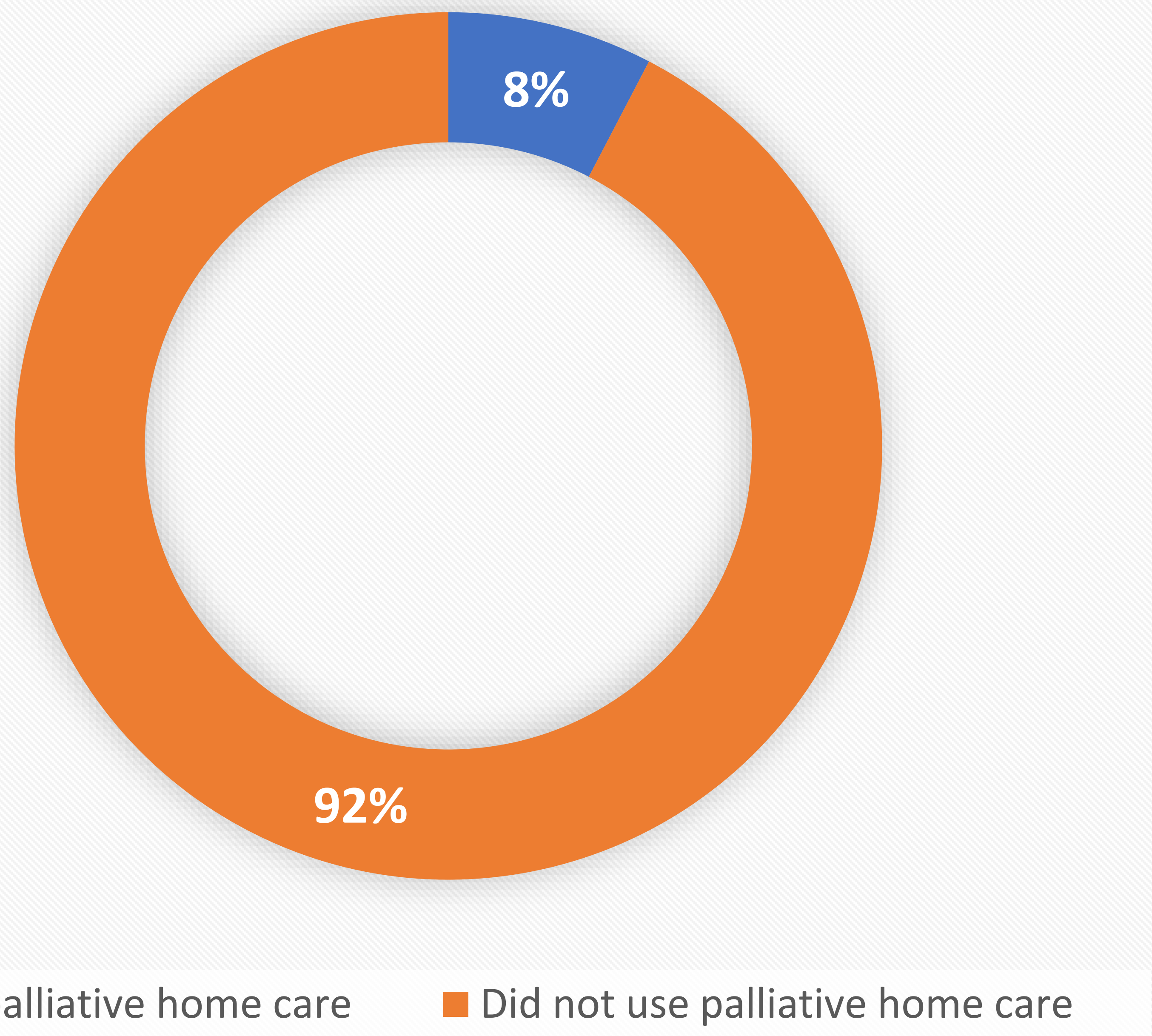
A slight shift towards earlier initiation



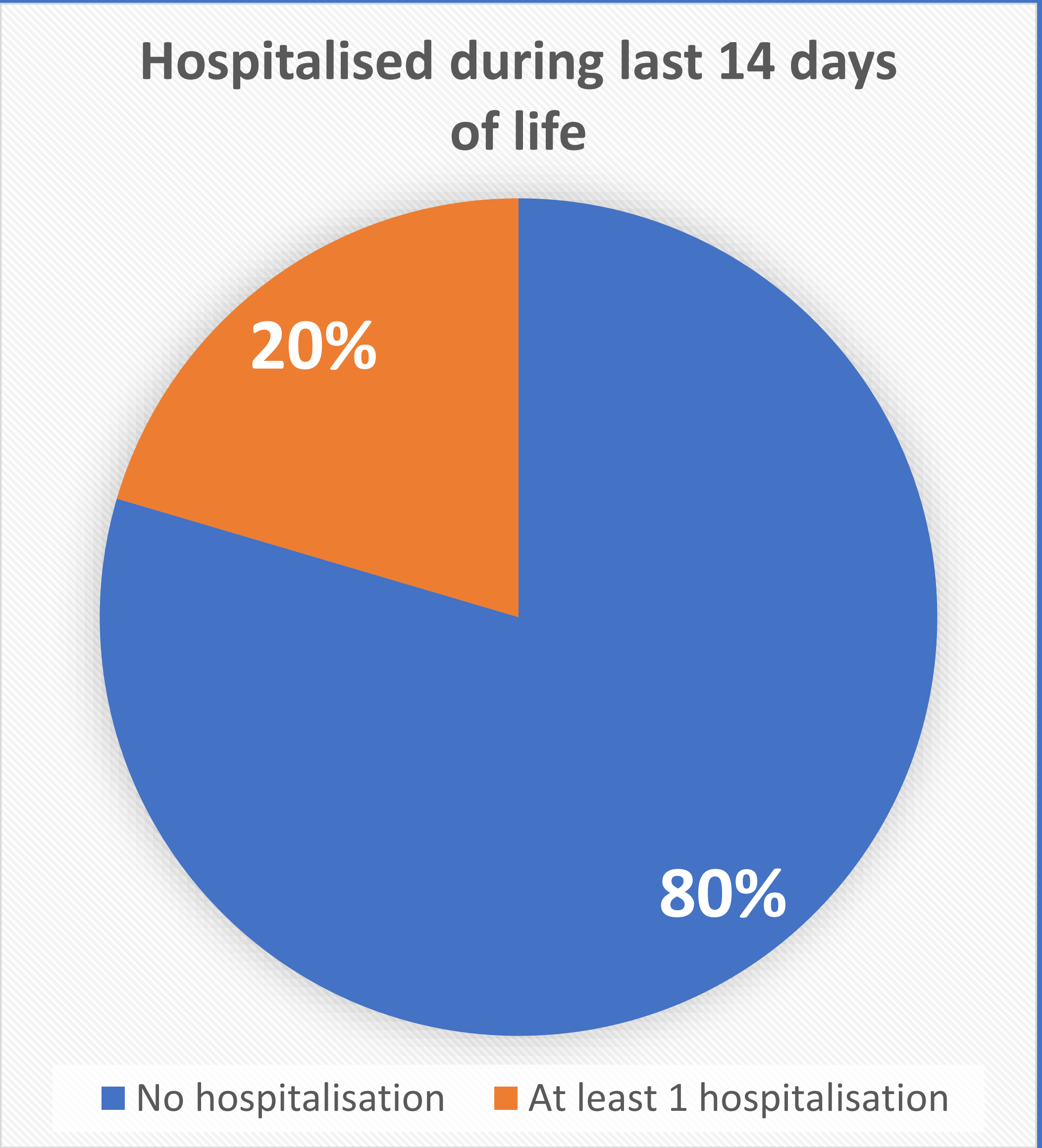
Function 4: Providing better evidence about effectiveness where this is difficult

What is the effect of using palliative home care on costs and appropriateness of end-of-life care?

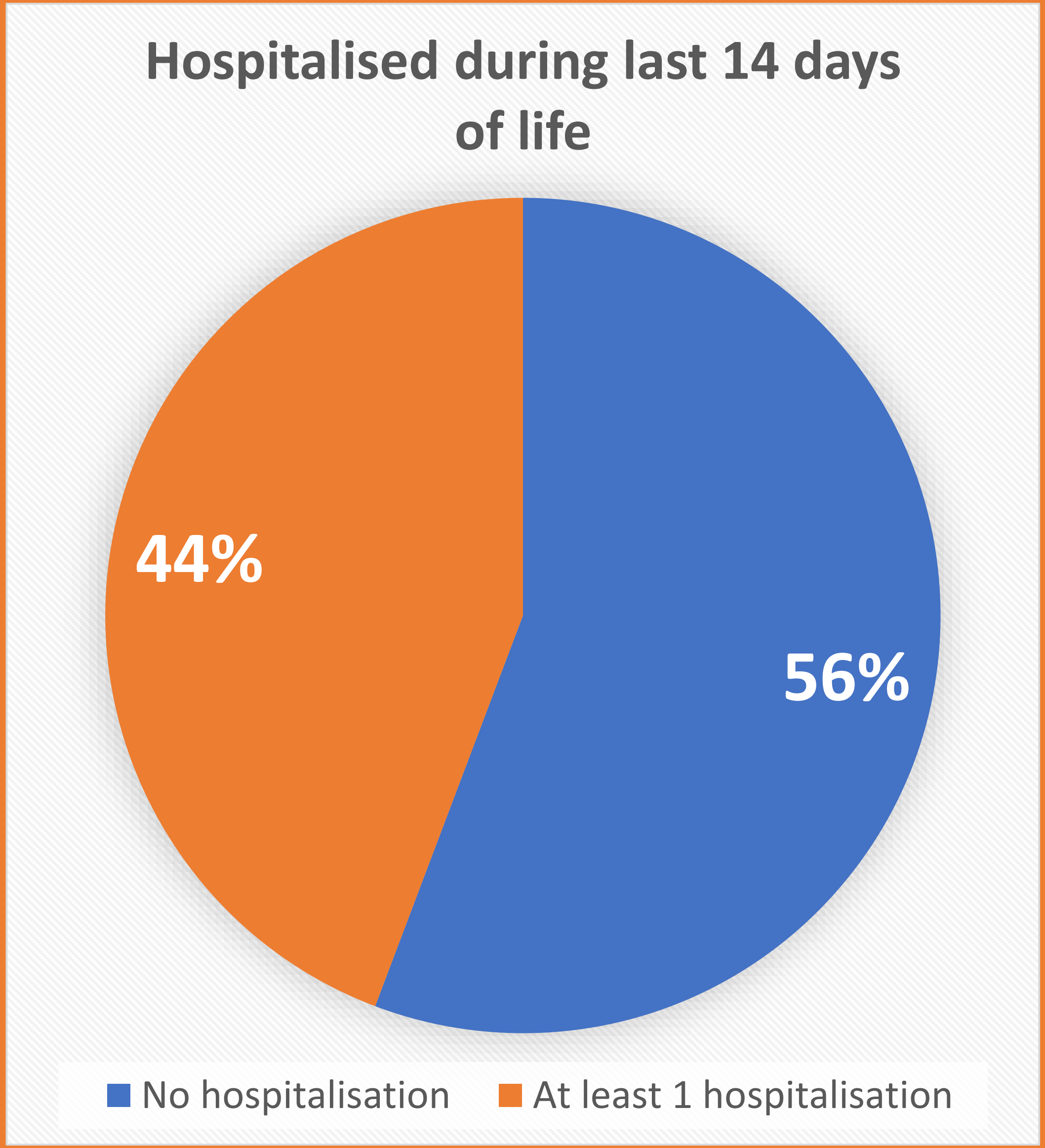
Data used: All deaths in Belgium in 2012 (n=107,847)



Persons who used PHC (n=8,256)



Persons who did not use PHC(n=99,591)



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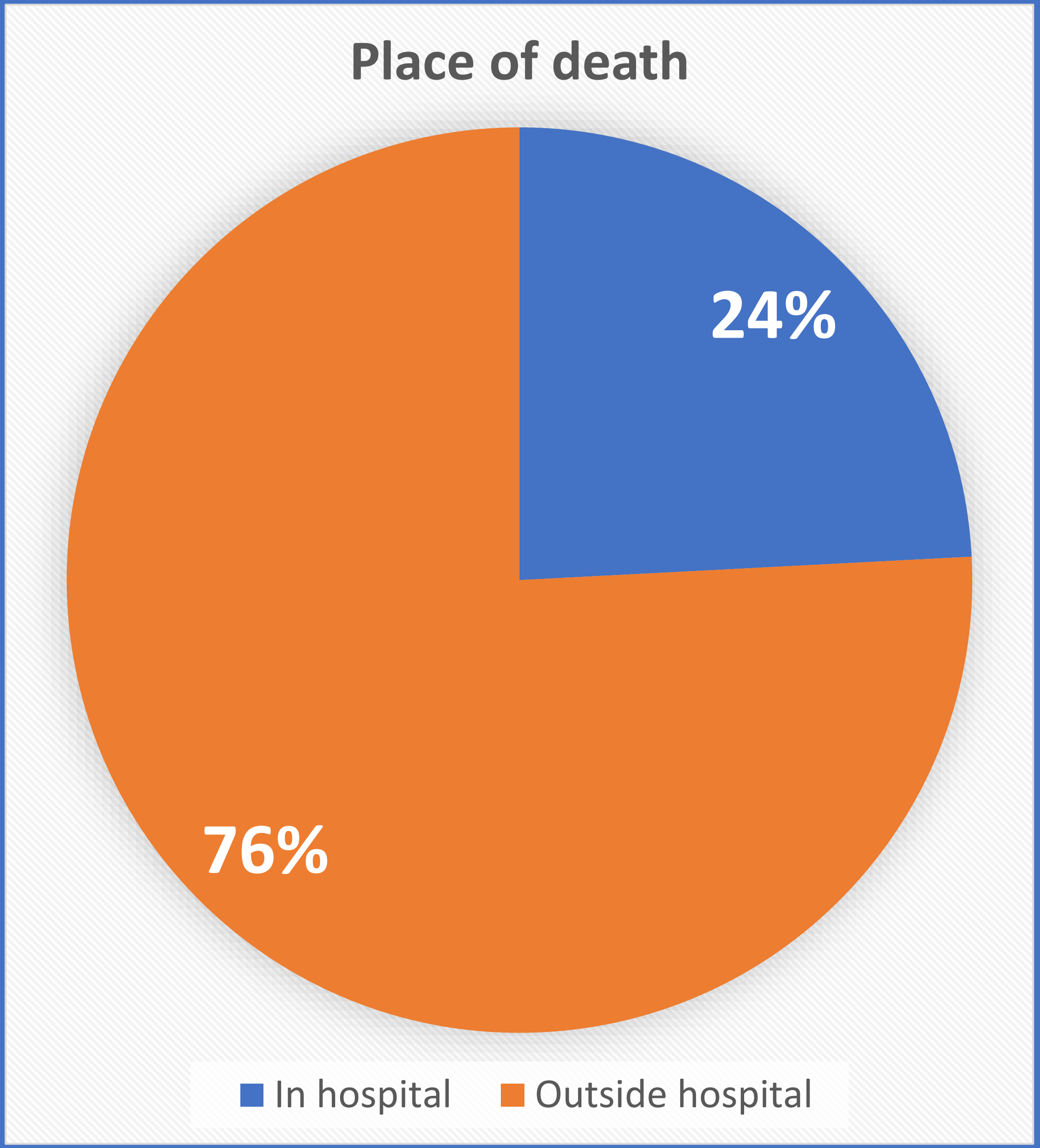

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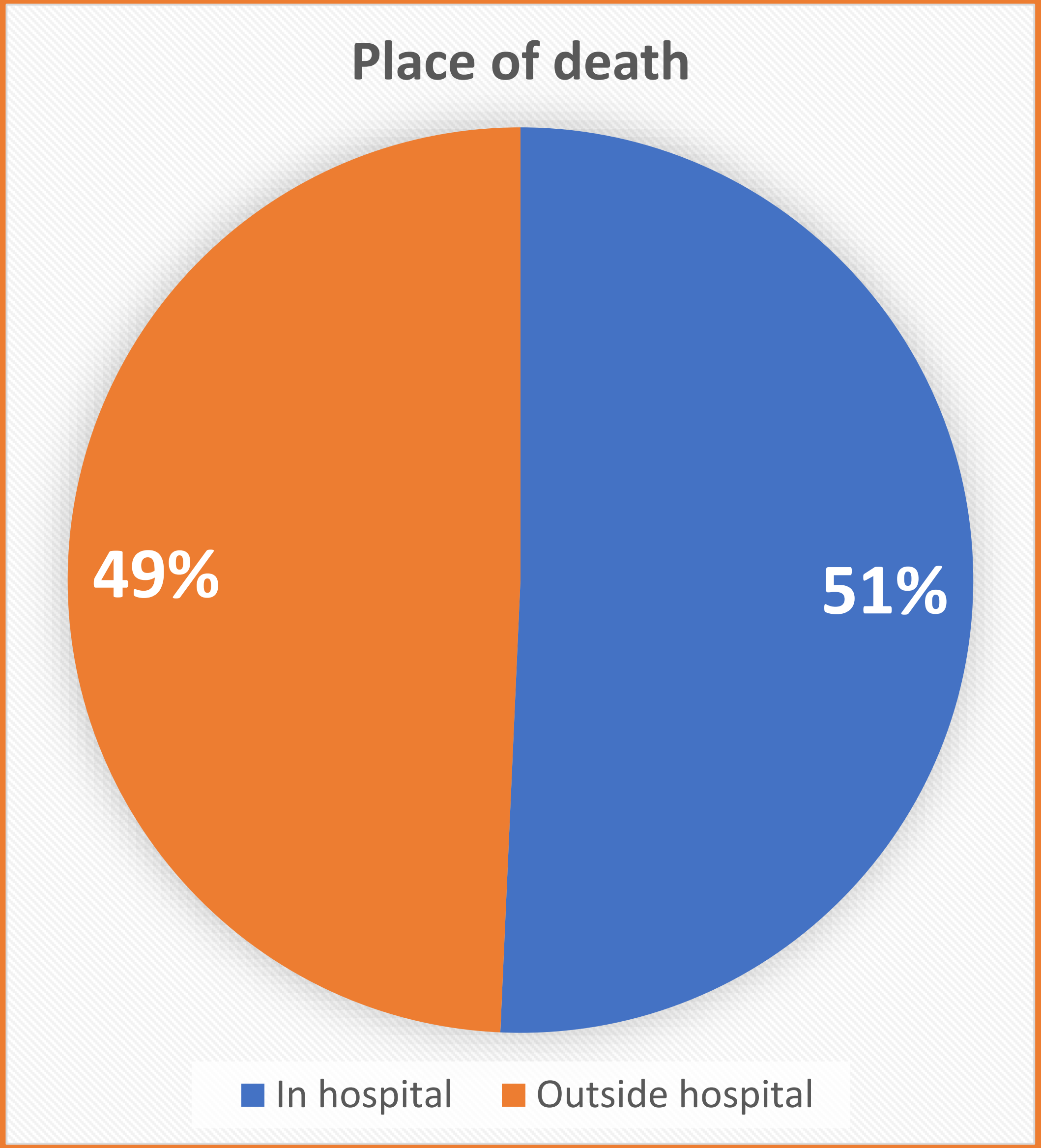
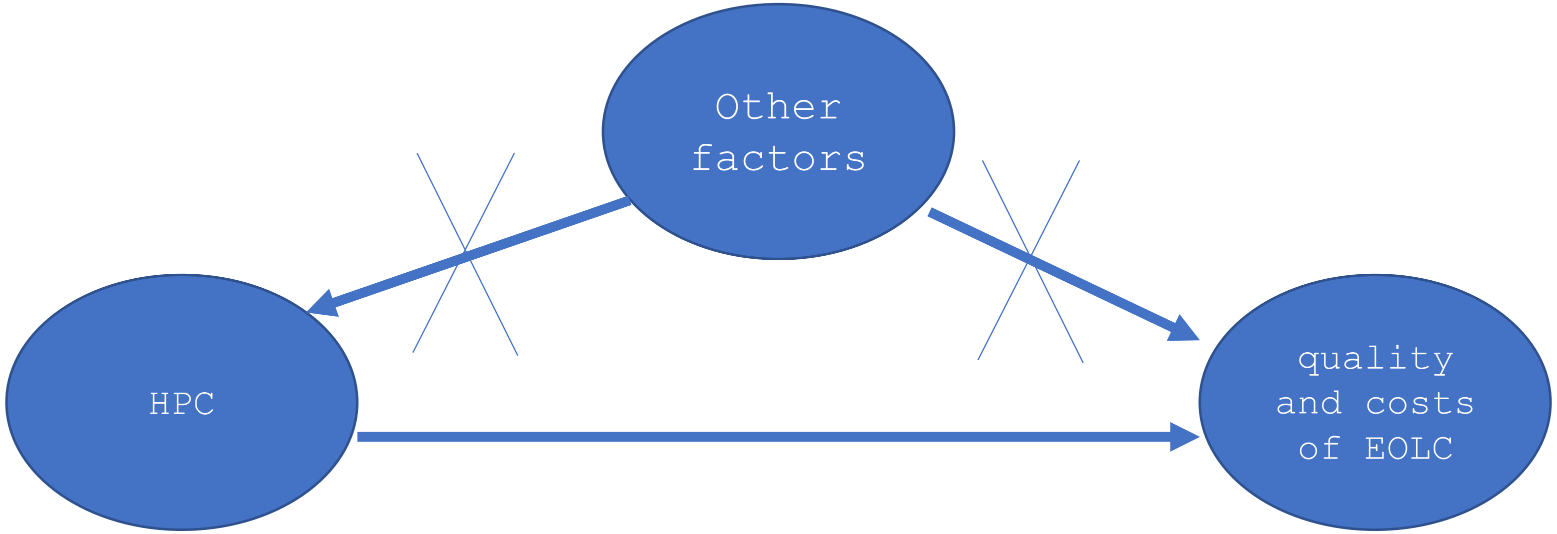


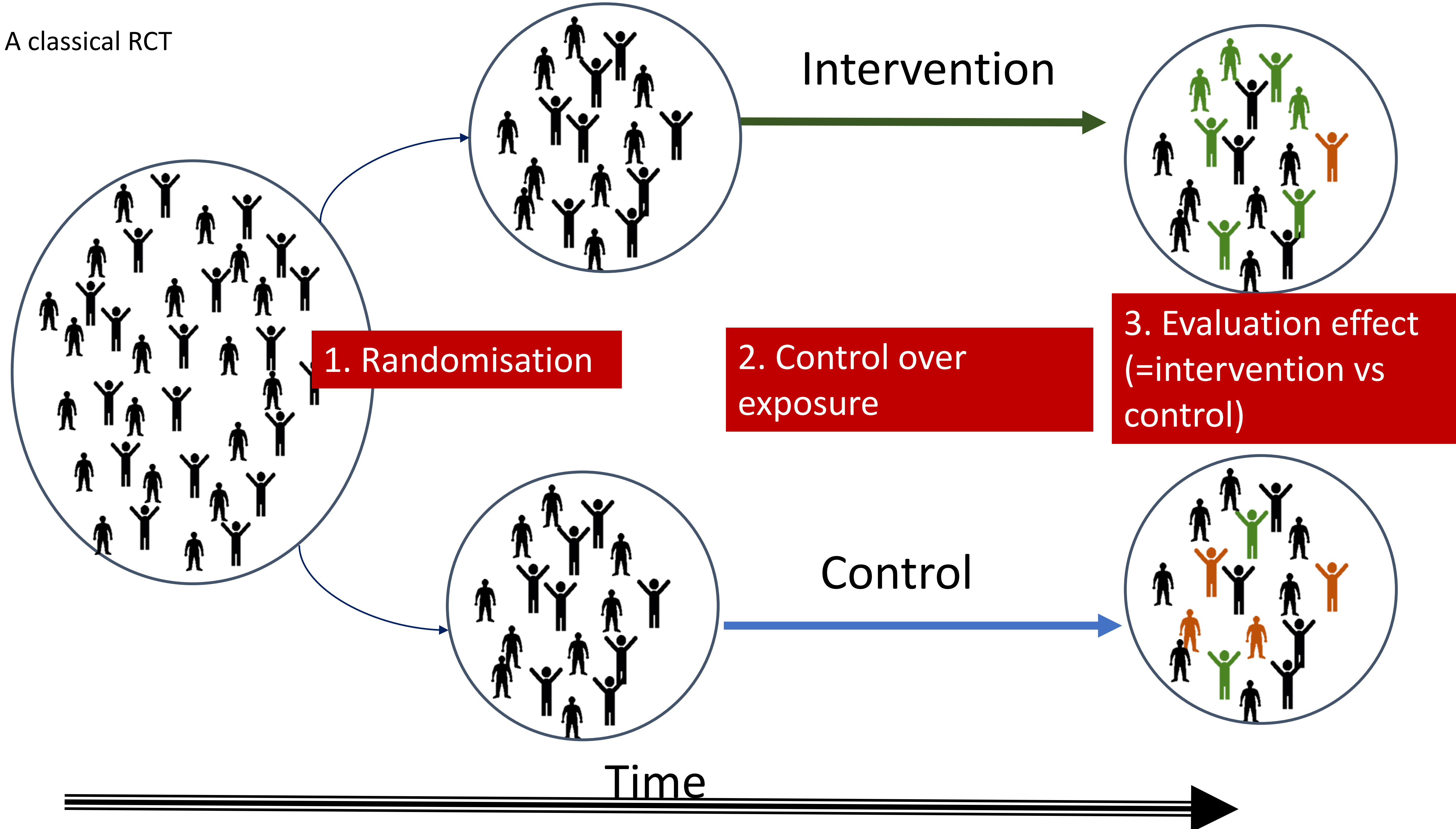
Problem: important conditions for causal effect are missing

1. Covariance

2. Temporality

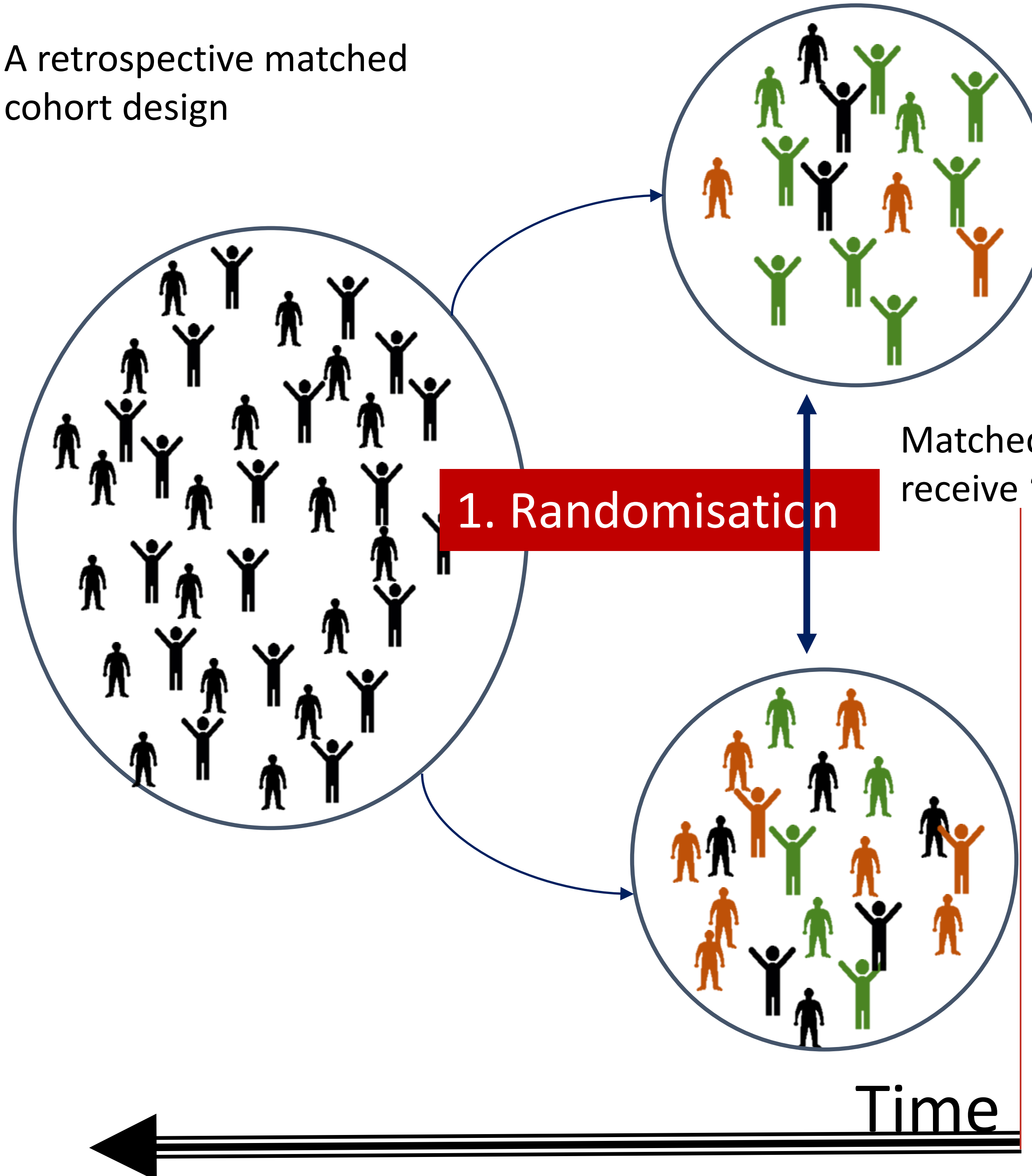
3. No confounding





A classical RCT
Intervention
1. Randomisation
2. Control over exposure
3. Evaluation effect (=intervention vs control)
Control
Time

A retrospective matched cohort design



Intervention

Matched for propensity to receive 'intervention'

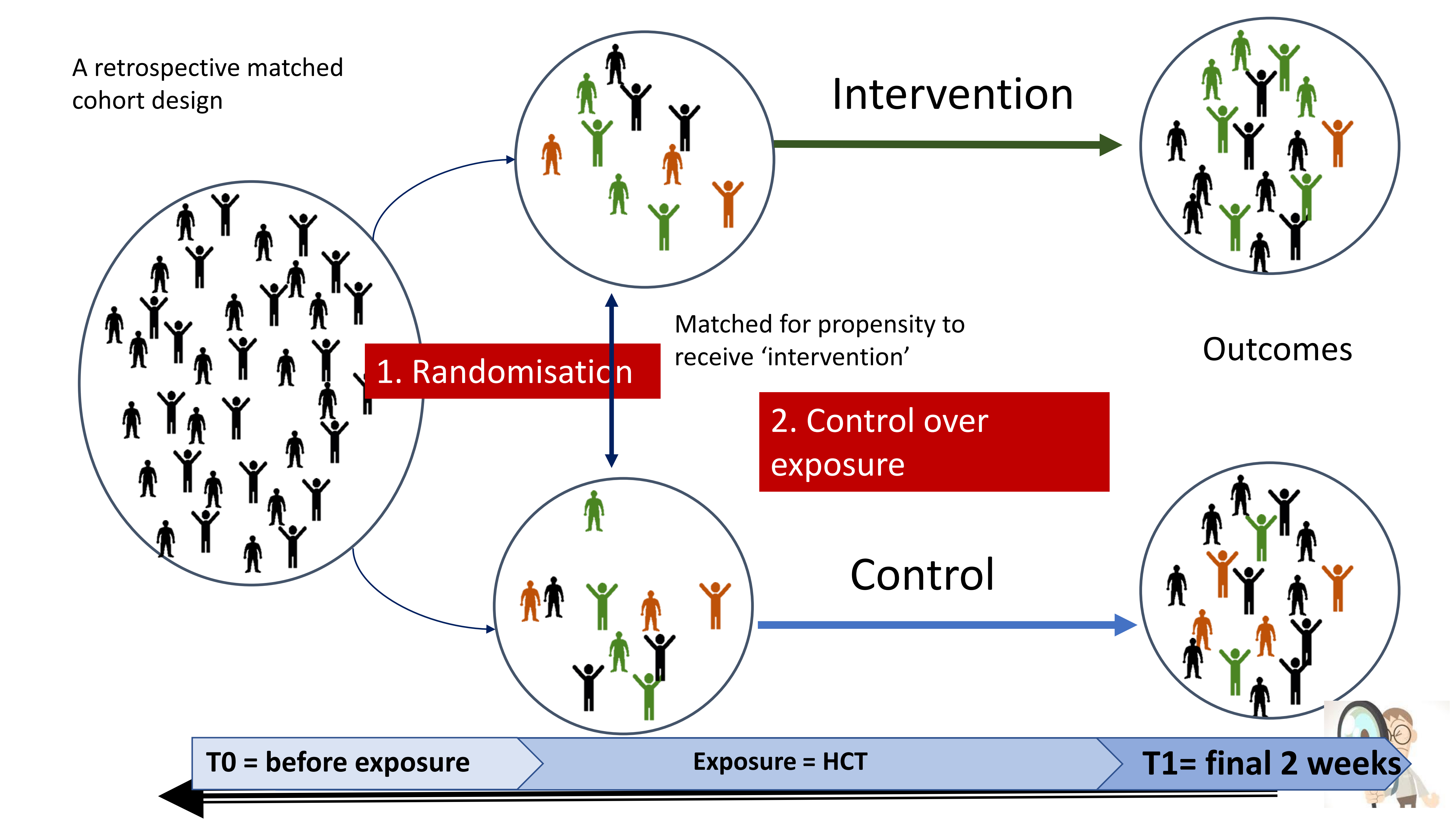
Outcomes

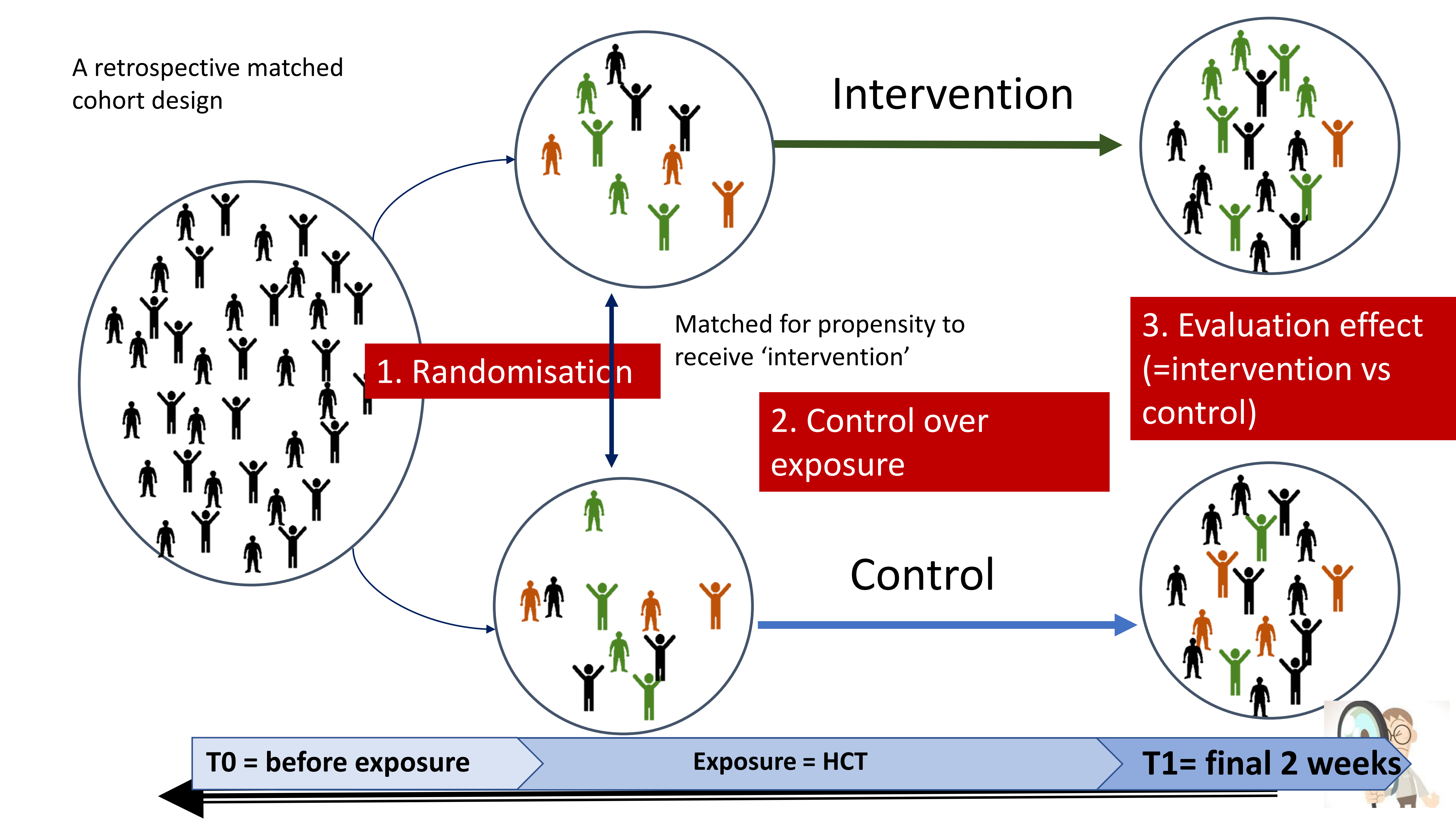
Matching the propensity score

Example data (fictional) N=9

Obs	Outcome	Propensity score:
1	Yes	0,77917
2	Yes	0,79674
3	No	0,17937
4	Yes	0,47309
5	No	0,83309
6	No	0,11435
7	No	0,47889
8	Yes	0,69812
9	No	0,74523

Calculated based on the confounders in the model


A retrospective matched cohort design
Intervention
1. Randomisation
Matched for propensity to receive ‘intervention’
Outcomes
2. Control over exposure
Control
T0 = before exposure
Exposure = HCT
T1= final 2 weeks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Control
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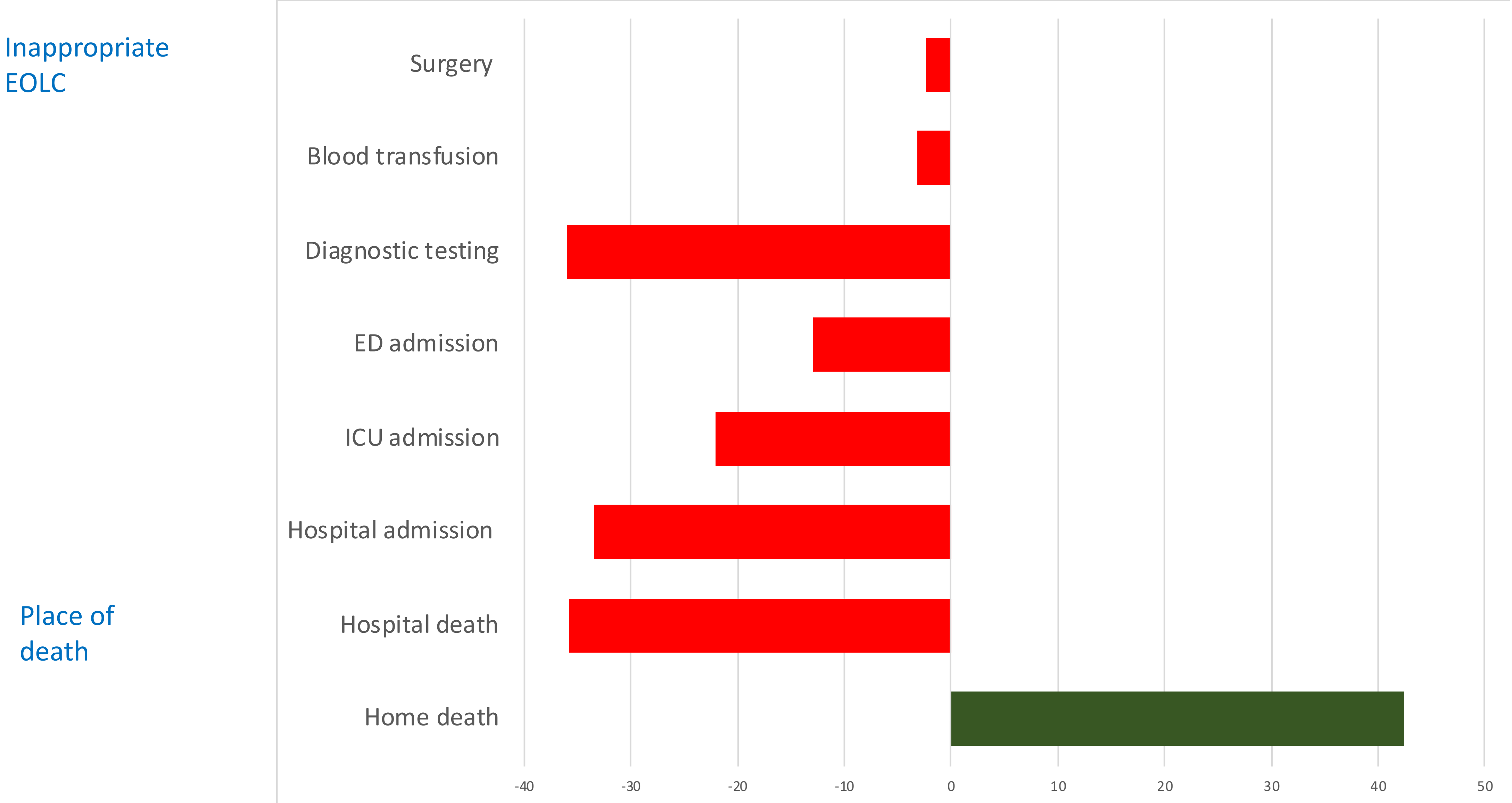
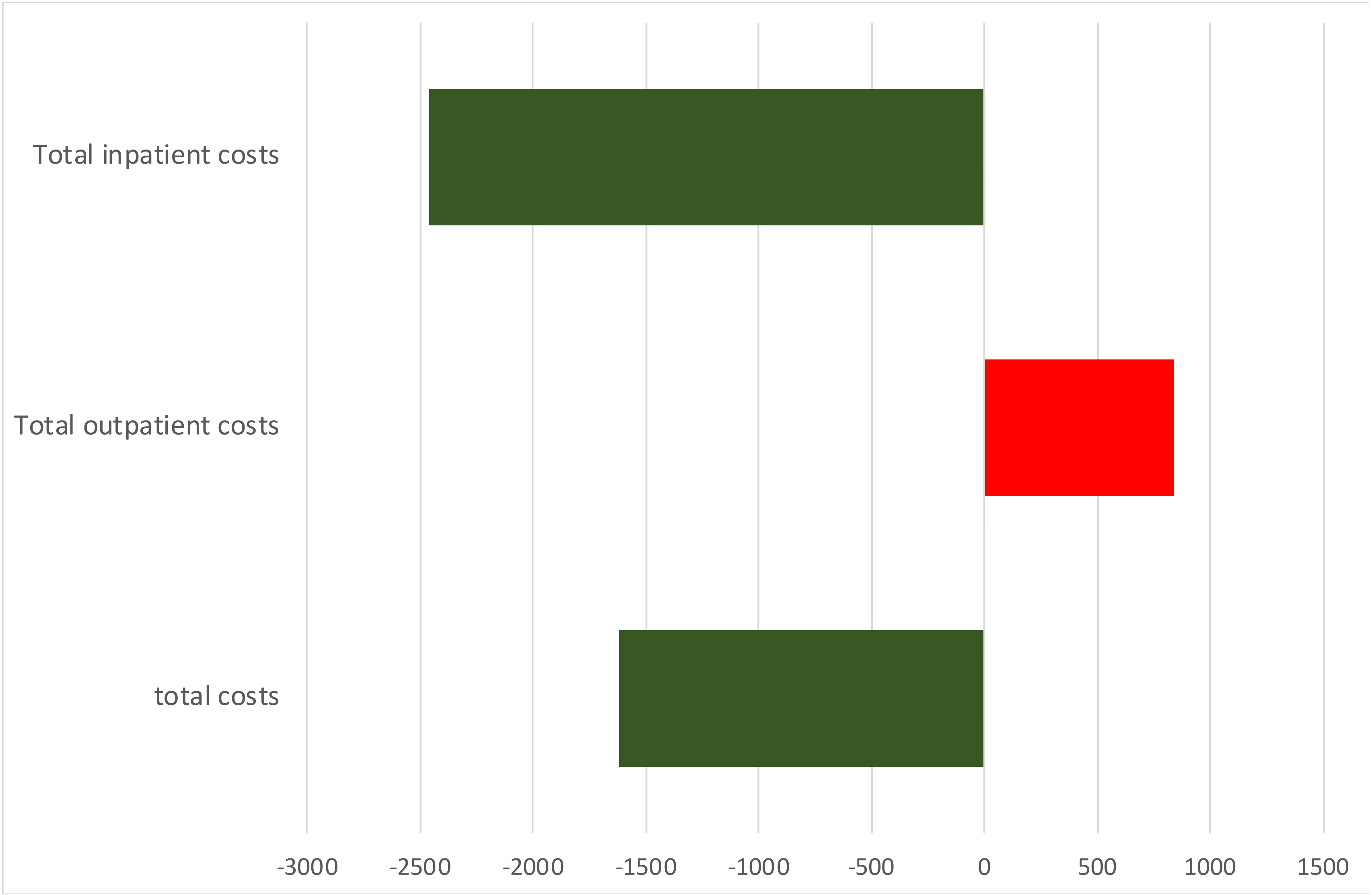
Use of palliative home care measures improves outcomes for quality EOLC in final 14 days



… and reduces the costs of care in final 14 days

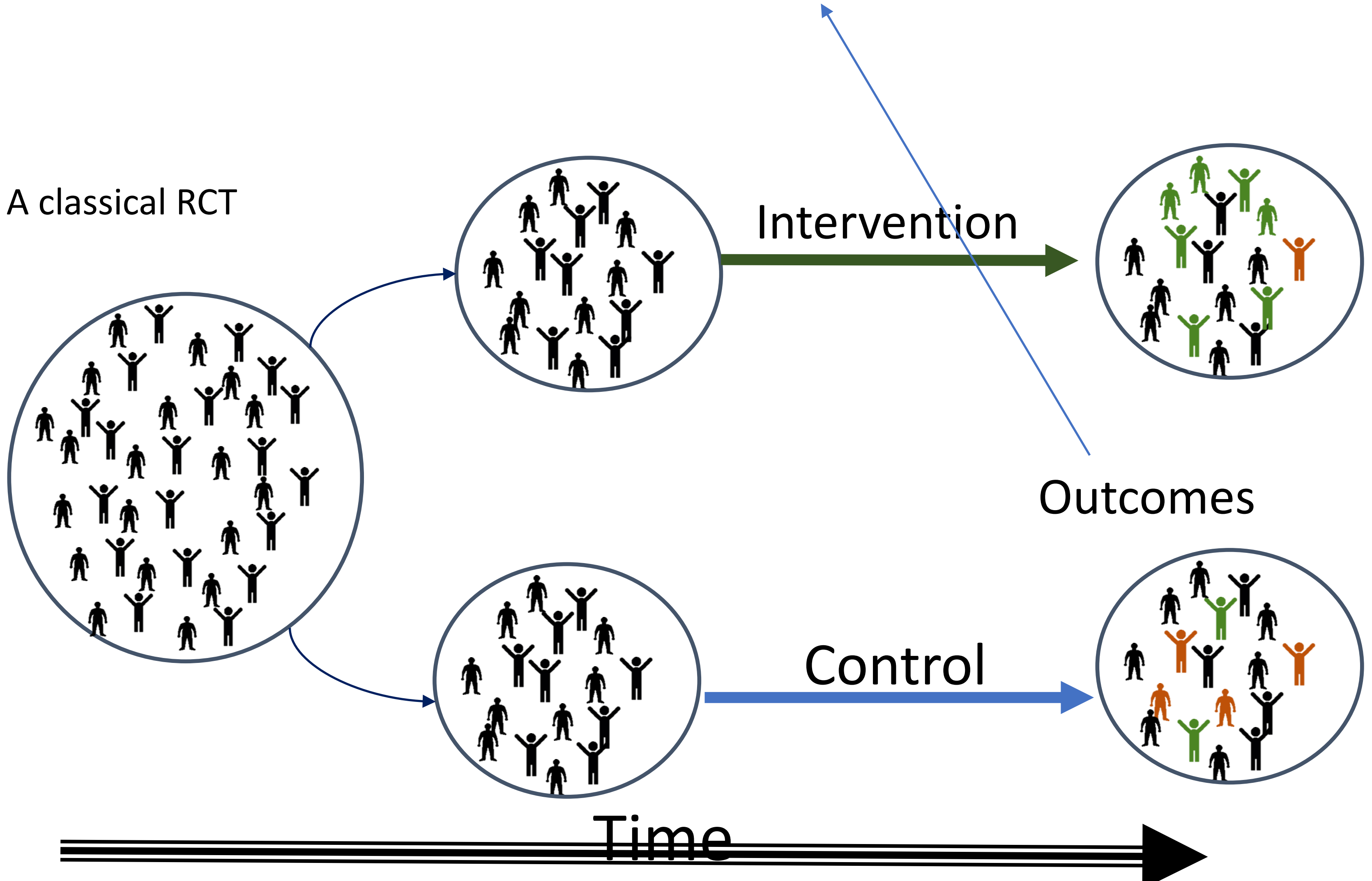


Function 4: Providing better evidence about effectiveness where this is difficult

Study on **EFFECT** of **SPOUSAL LOSS** on **HEALTH OUTCOMES**? Sweden

Function 5: More efficient RCTs

Big data provides data
→Fewer missings / drop-out problem
→Less burdening data-collection
→Less expensive



Function 6: Algorithms for prediction and prospective decision support

Improving Palliative Care with Deep Learning

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Abstract— **Improving the quality of end-of-life care for hospitalized patients is a priority for healthcare organizations. Studies have shown that physicians tend to over-estimate prognoses, which in combination with treatment inertia results in a mismatch between patients wishes and actual care at the end of life . We describe a method to address this problem using Deep Learning and Electronic Health Record (EHR) data, which is currently being piloted, with Institutional Review Board approval, at an academic medical center. The EHR data of admitted patients are automatically evaluated by an algorithm, which brings patients who are likely to benefit from palliative care services to the attention of the Palliative Care team. The algorithm is a Deep Neural Network trained on the EHR data from previous years, to predict all-cause 3-12 month mortality of patients as a proxy for patients that could benefit from palliative care. Our predictions enable the Palliative Care team to take a proactive approach in reaching out to such patients, rather than relying on referrals from treating physicians, or conduct time consuming chart reviews of all patients. We also present a novel interpretation technique which we use to provide explanations of the model's predictions.**

sive care. Second, a shortage of palliative care professionals makes proactive identification of candidate patients via manual chart review an expensive and time-consuming process.

The criteria for deciding which patients benefit from palliative care can be hard to state explicitly. Our approach uses deep learning to screen patients admitted to the hospital to identify those who are most likely to have palliative care needs. The algorithm addresses a proxy problem - to predict the mortality of a given patient within the next 12 months - and use that prediction for making recommendations for palliative care referral. This frees the palliative care team from manual chart review of every admission and helps counter the potential biases of treating physicians by providing an objective recommendation based on the patient's EHR. Currently existing tools to identify such patients have limitations, and they are discussed in the next section.

II. Related Work

What can big data do for compassionate communities?

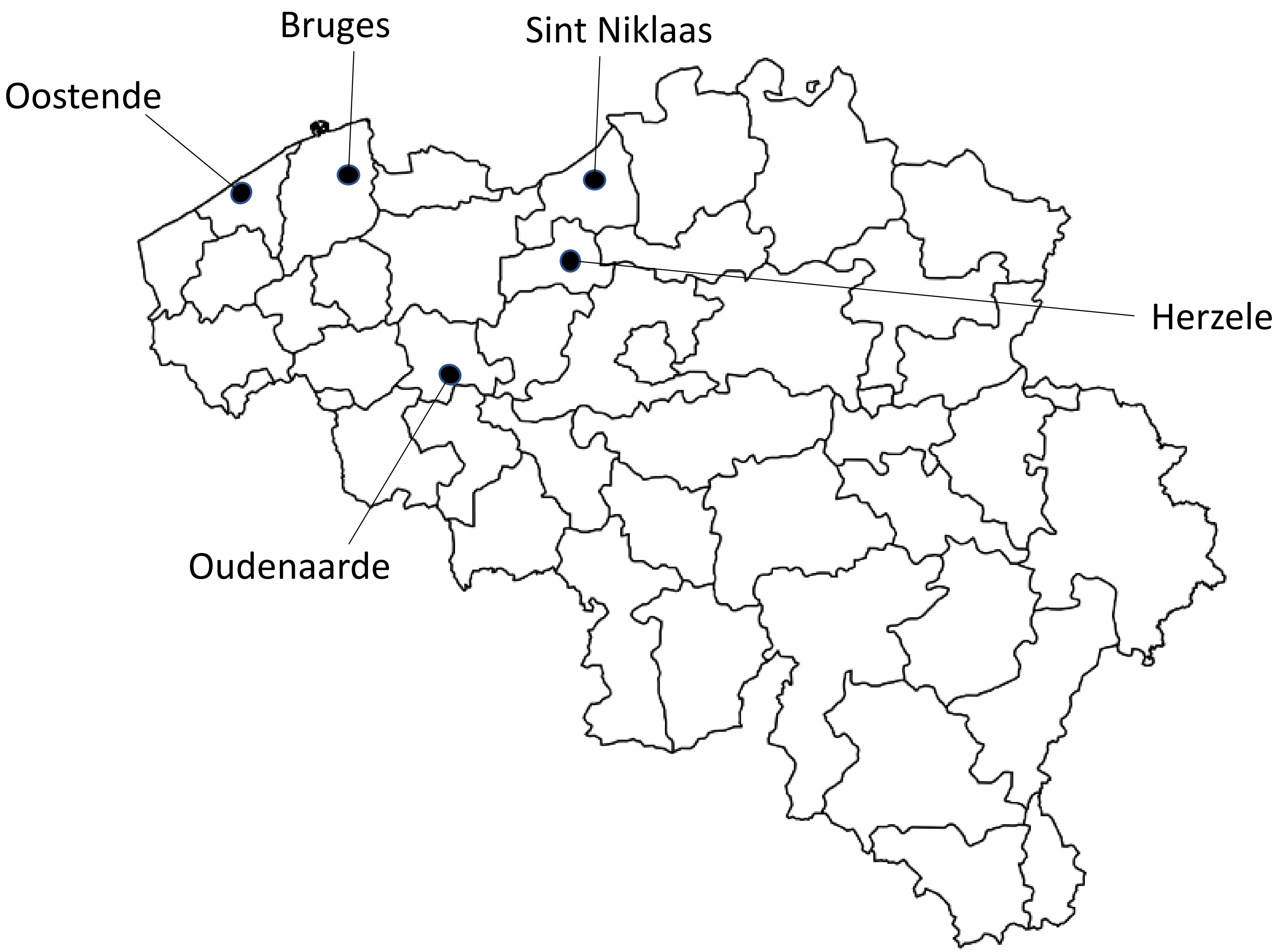
Assist in addressing various public health functions:

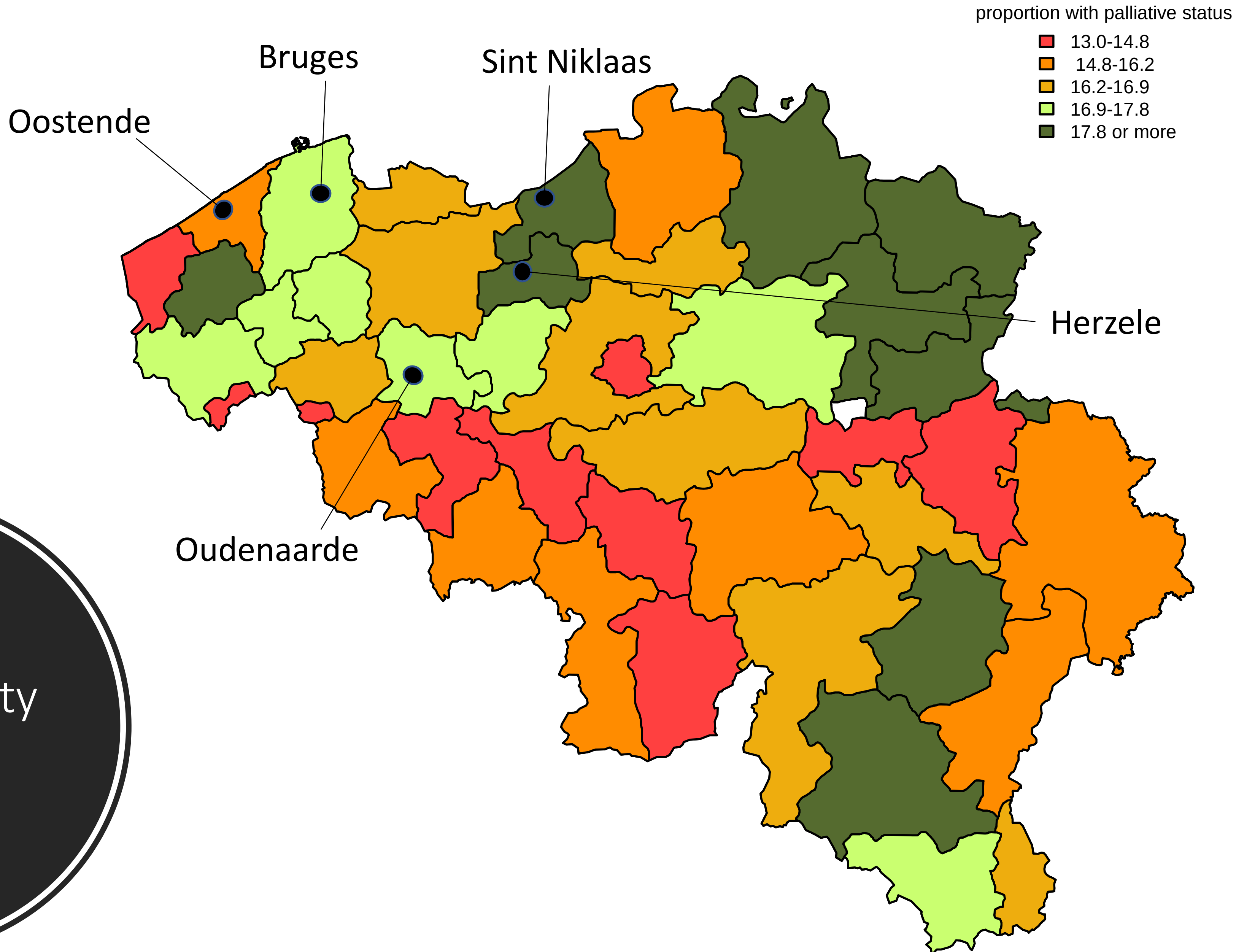
1. Population diagnosis
2. Outcome evaluation

Evaluation framework for comcoms

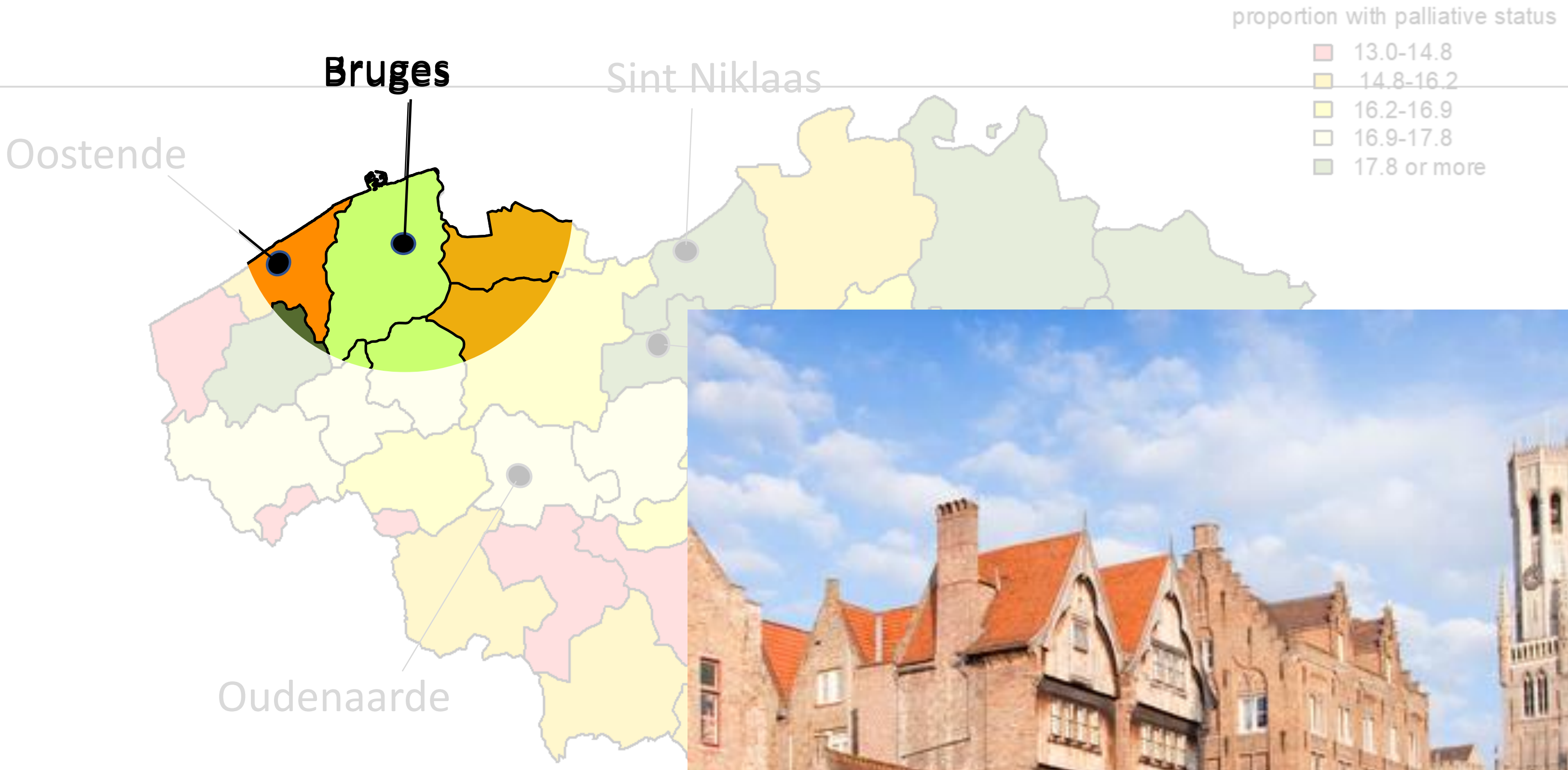
Structures	**Process: activities**	**Output: Short-term achievements**	**Outcomes: Longer-term achievements**
• Organizational capacity • Resources, funding • Intersectoral partnerships • Community ownership	• policy development actions • Actions to create supportive environments • Education activities • Community engagement activities • Health services interactions • Planning strategy • Project evaluations	• Activities completed • Project objectives met? • **Compare** knowledge, attitude and practice change **before and after** activity	• individual, community or environmental health outcomes that are likely to take a longer period to achieve
Examples of Indicators ✓ Project office ✓ Steering committee ✓ …	**Examples of Indicators** ✓ Community diagnosis ✓ Activities implemented (eg nr of workshops, seminars ✓ Nr of target recipients involved in activities ✓ …	**Examples of Indicators** ✓ Nr of schools, workplaces etc with policies ✓ Activities taking place within each of the Ottawa pillars ✓ Increased death literacy ✓ Increased social capital ✓ Increased experiential learning	**Examples of Indicators:** ✓ Improvement in quality of EOLC ✓ Improved bereavement experiences, support for family caregivers

Candidate compassionate cities in Belgium

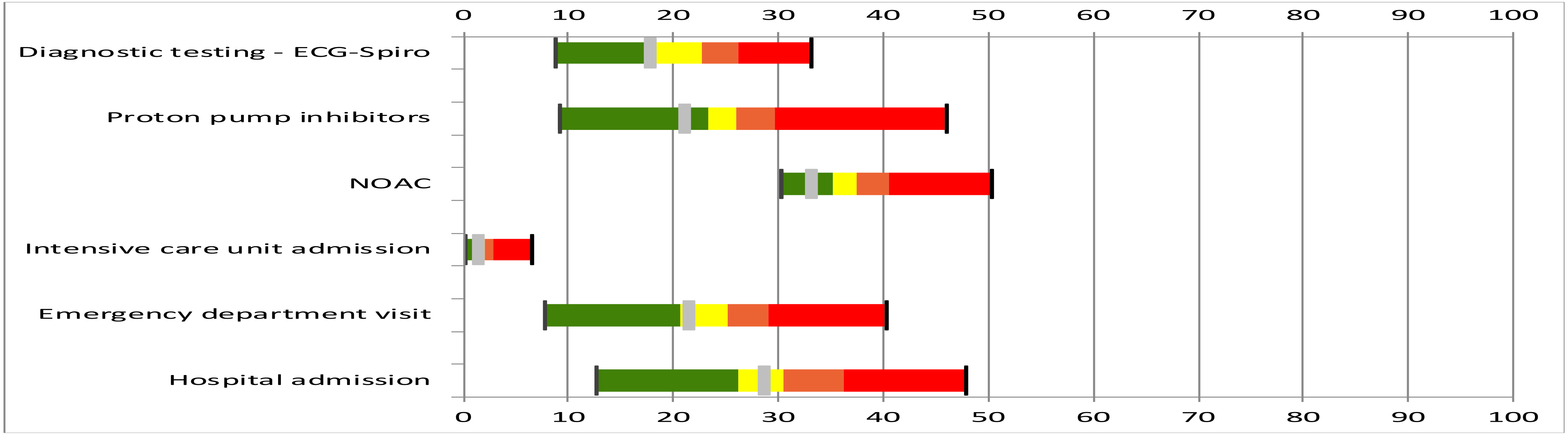


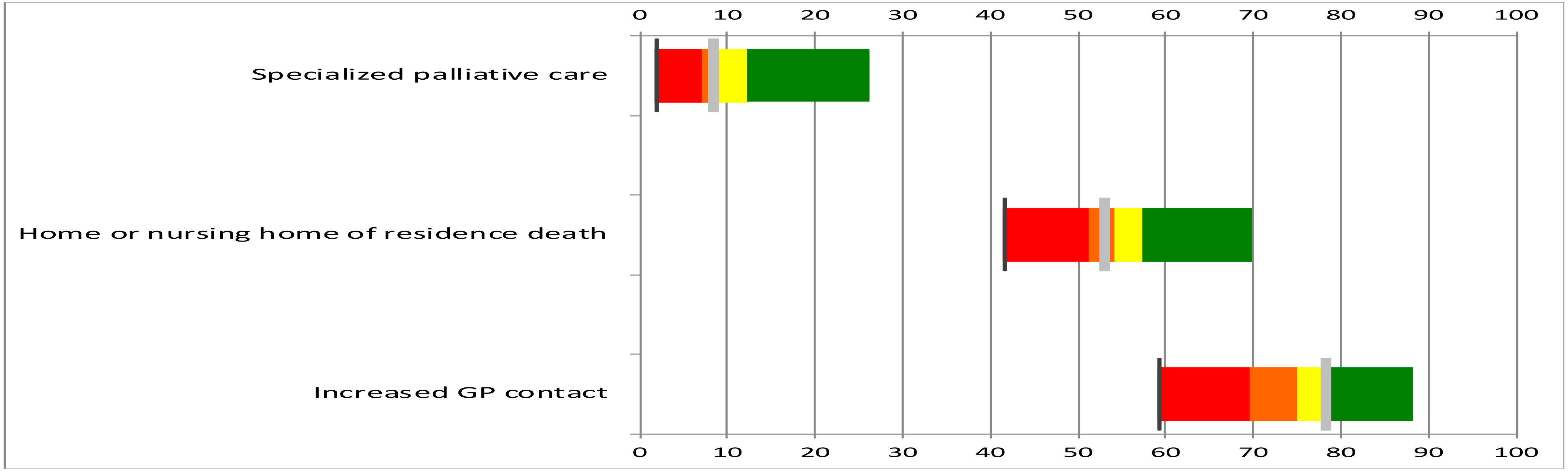


1: community diagnosis

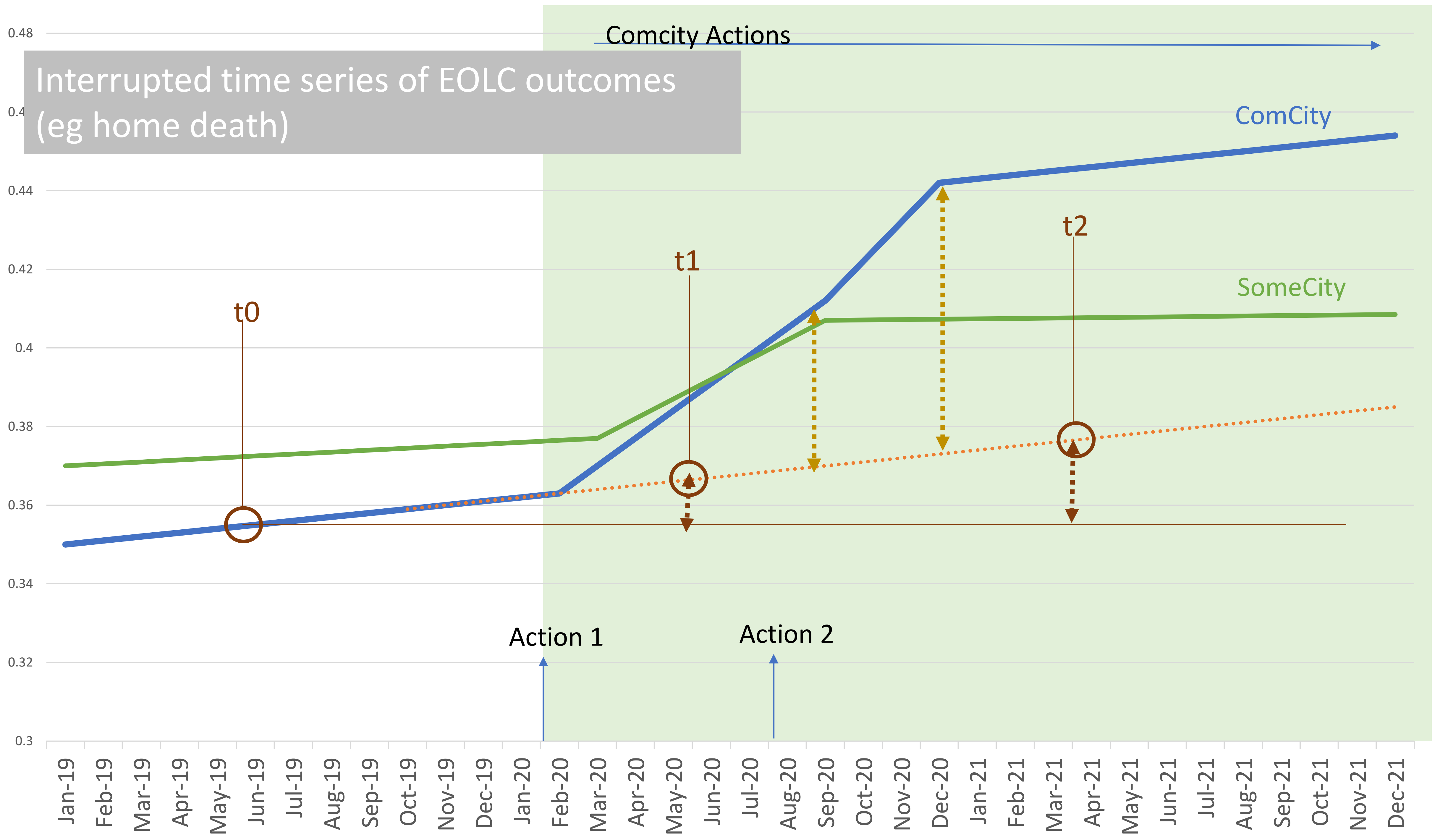

proportion with palliative status
13.0-14.8
14.8-16.2
16.2-16.9
16.9-17.8
17.8 or more
Bruges
Sint Niklaas
Oostende
Oudenaarde

Diagnosis of Bruges (quality EOLC QIs dementia)





2: outcome evaluation



Interrupted time series of EOLC outcomes (eg home death)
Comcity Actions
ComCity
SomeCity
t0
t1
t2
Action 1
Action 2
0.48
0.44
0.42
0.4
0.38
0.36
0.34
0.32
0.3
Jan-19
Feb-19
Mar-19
Apr-19
May-19
Jun-19
Jul-19
Aug-19
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
Mar-20
Apr-20
May-20
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Oct-20
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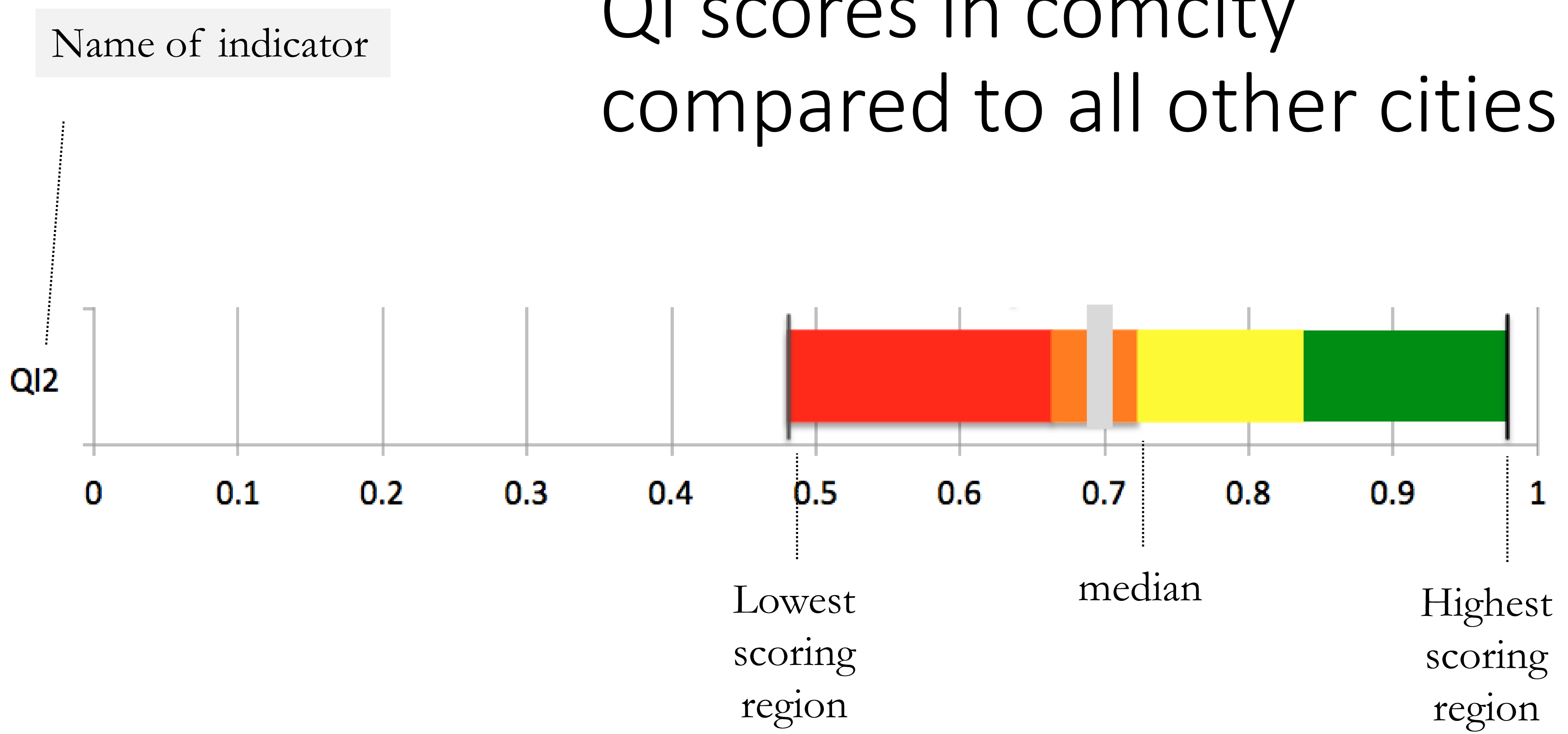
Dec-20
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

Improvement in **risk-adjusted** QI scores in comcity compared to all other cities



Conclusions

Big data can help the public health palliative care research agenda by:

1. assessing and monitoring need
2. quality of care evaluations
3. evaluation of policies, interventions, programs (including comcom!!)
4. providing evidence about effectiveness where this is difficult
5. enabling more efficient RCTs
6. working towards algorithms for prediction and prospective decision support

Limitations need to be acknowledged

Only provides one type of evidence