JA PreventNCD
Joint Action Prevent Non-Communicable Diseases

Task 8.4 c: Modelling health care costs at micro-economic level

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Outline

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- **Objectives** of cost data modelling
- Main **features of medical cost data**
- Review of the main **regression approaches** for medical cost data
- **Weighted gamma regression (WGR)**: motivations and advantages
- **Application** of WGR to colon cancer cost data from Italian registries
- **Conclusions**

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Outcome of interest

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Outcome variable = individual annual cost of colon cancer patients

Our modelling analyses are distingued by:

- **the 3 annual phases of care (POCs)**:
  - **initial** (12 months from diagnosis)
  - **continuing** (6 months before to 6 months after the prevalence date)
  - **final** (12 months before death)
- **the 3 main healthcare services**:
  - **hospital admission (HA)**
  - **out-patient services (OPS)**
  - **territorial drug-prescriptions (DP)**

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Cost drivers

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The main factors affecting medical expenses include

- **patient's socio-demographics**: *gender, age*
- **clinical conditions**: *disease subtype and stage, distance from diagnosis, comorbidities (Charlson index)*
- **treatment practices**: *number of treatments, treatment type*
- **geographical variation**: *cancer registry* (CR)
    - *treatment providers*
    - *local assistance administrations*
    - *regional insurance reimbursement rates*

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Objectives

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A statistical modelling analysis of healthcare expenses data aims to

- **quantifying** the economic burden and **describe the variability** of cost data
- **identifying the determinants** of healthcare costs
- **making predictions** of cost impact under specific scenarios and interventions

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Features of medical cost data

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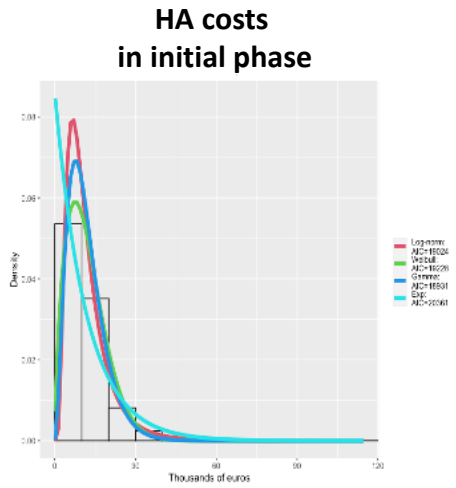
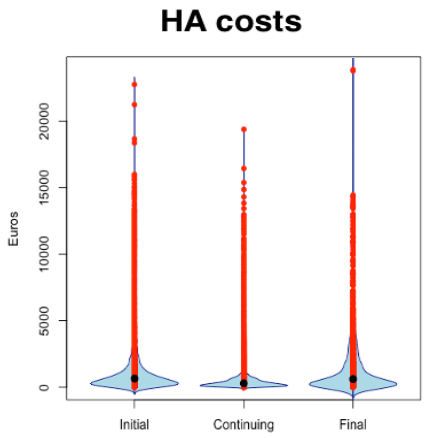
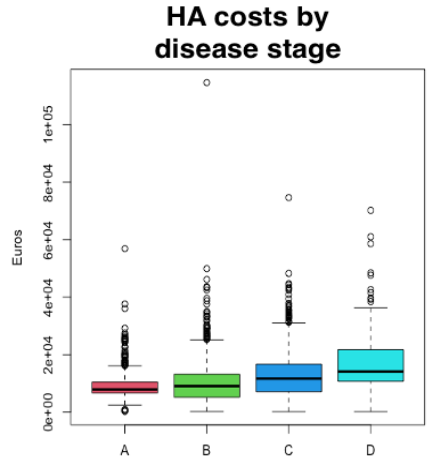
Healthcare expense data are typically characterized by

- **right-skewness**: remarkable asymmetric distribution with a long heavy right tail
- **heteroscedasticity (non-constant variance)**: induced by one of more covariates
- **outliers**: patients with an atypically high amount of expenses







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Features of medical cost data

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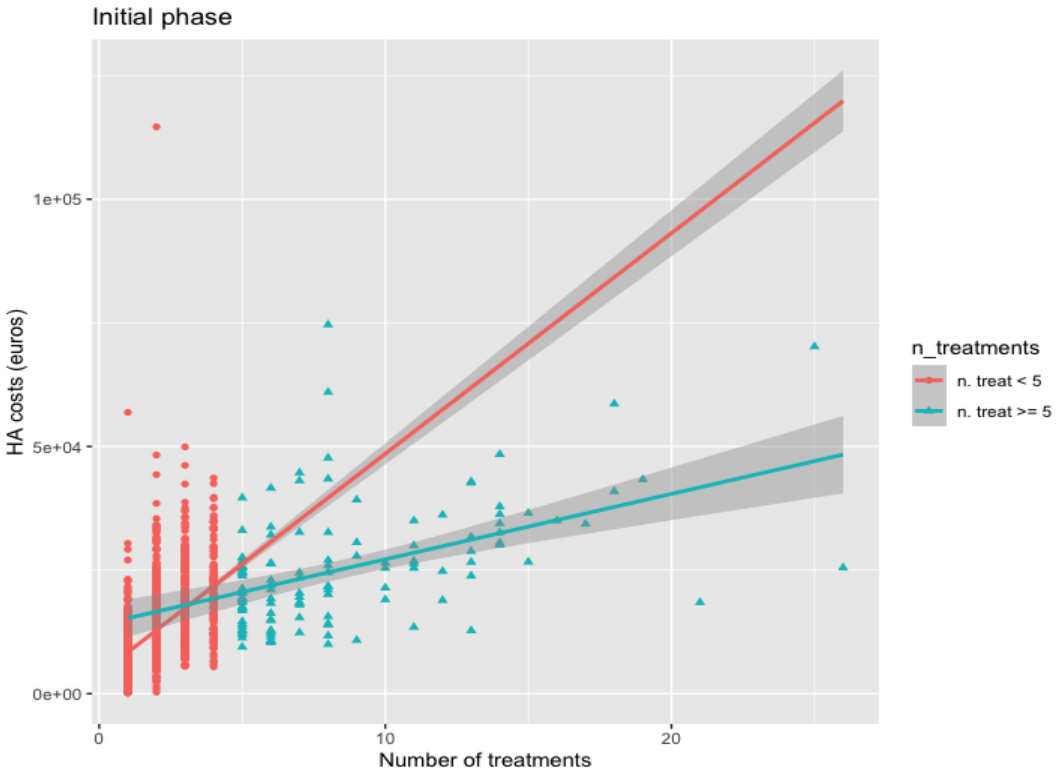

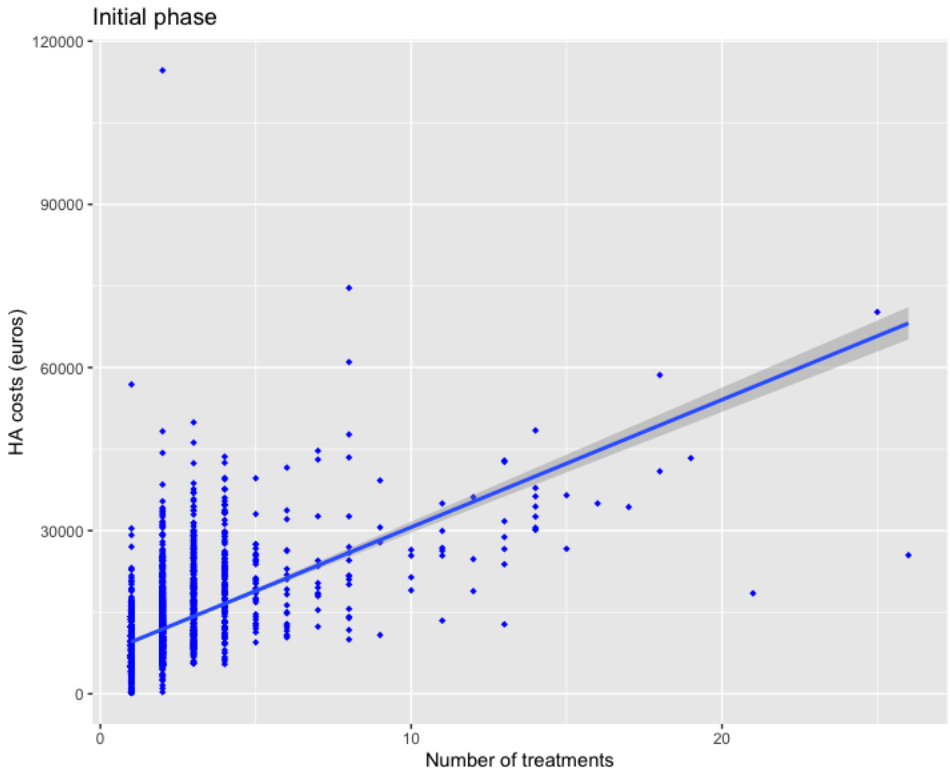

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Statistical modelling issues

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Inadequacy of standard regression modelling approaches due to lack of robustness to

- **departures from the underlying assumptions**: biased and inconsistent estimates
- **presence of outliers**: maximum likelihood estimates are attracted by deviating observations

Need of suitable statistical methods to obtain reliable estimates!

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Brief review of cost data models

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A variety of strategies have been proposed in the literature

- **data-transformation**: typically the log-transformation to mitigate skewness and heteroscedasticity
- **Generalized linear models (GLM)**: relaxation of the normality assumption in favour of the more general exponential family (for example, Gamma and Weibull)

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Robust regression model

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We opt for a weighted regression model that

- **fits cost data on the original scale**
  - to gain a direct interpretability
  - to avoid the retransformation bias
- **accounts for heteroscedasticity**
- **incorporates the information provided by outliers** in a robust way

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Weighted Gamma regression with log link

We propose to use the **weighted gamma regression (WGR)** with log link (Cantoni and Ronchetti, 2006)

- **right-skewness is captured** by the asymmetric shape of the Gamma density
- **heteroscedasticity is automatically addressed** by the mean-variance relationship of the Gamma density

$$E(Y_i \mid x_i) = \mu_i \qquad VAR(Y_i \mid x_i) = c\,\mu_i^2$$

where μ_i denotes the individual expected cost of patient *i*. The WGR, hence, postulates heteroscedasticity

$$\log(\mu_i) = \mathbf{x}'_i\boldsymbol{\beta} \implies VAR(Y_i \mid x_i) = c\exp(\mathbf{x}'_i\boldsymbol{\beta})$$

- **weighted least squares estimation procedure** $\Longrightarrow$ outliers are downweighted $(\omega_i < 1)$

Cantoni and Ronchetti (2006). A robust approach for skewed and heavy-tailed outcomes in the analysis of health care expenditures. Journal of Health Economics, 25(2), 198-213.

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Weighted Gamma regression with log link

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- **more flexible tool:** compromise between completely excluding outliers from the sample and including all the observations in the inferential process by assigning them the same importance
- **no artificial inflation of the regression coefficient SEs:** possibility to highlight significant effects which are lost with the classic Gamma regression
- the relative weights provide a **diagnostic tool for outlier detection**

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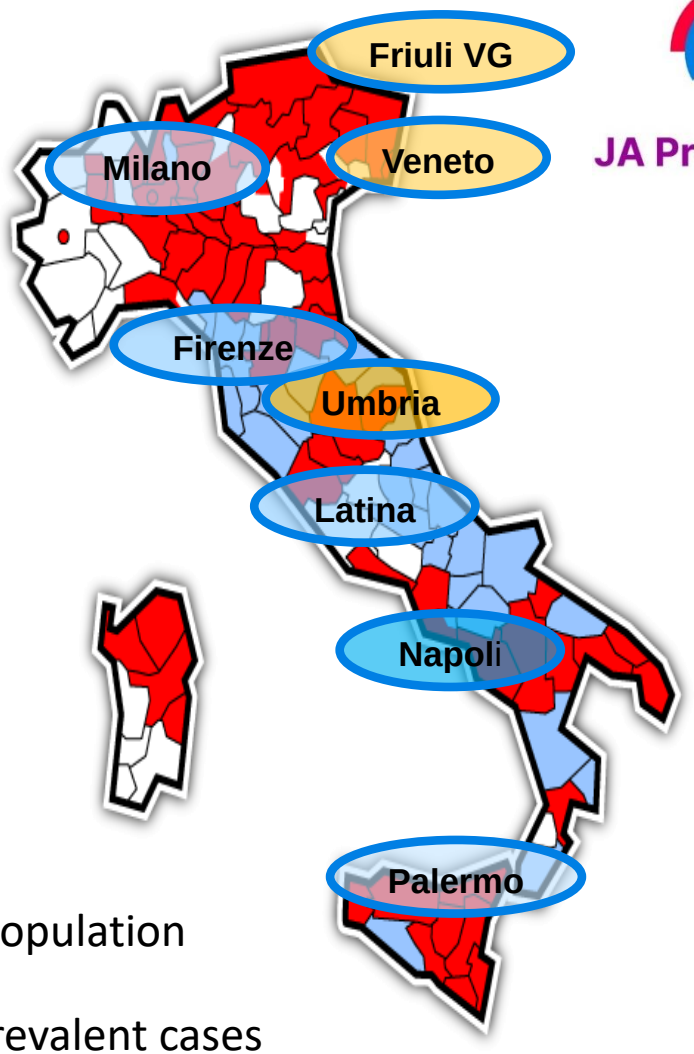
Data sources

We analyze colon cancer data from **8 cancer registries** (CRs), namely

1. **Firenze**
2. **Friuli Venezia Giulia**
3. **Latina**
4. **Milano**
5. **Napoli**
6. **Palermo**
7. **Umbria**
8. **Verona**



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- covering over 10 million people, thus about one sixth of the Italian population
- coming from **EPICOST 1** project including a study cohort of 21,542 prevalent cases
- diagnosis of a malignant colon Cancer (ICD9-CM C18) in referred to the period 2010–2011

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Data sources

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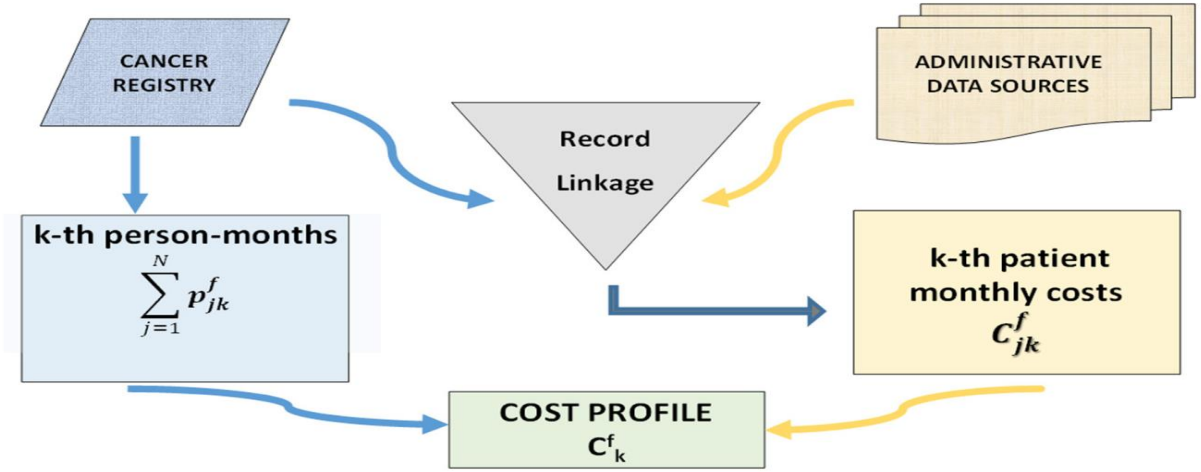
Information from the **CRs were linked with 3 administrative databases of healthcare services**:

- **Hospital Admission** (**HA**, or SDO in ita.)
- **Outpatient Services** (**OPS**, or SPA in ita.)
- **Drug Prescriptions** (**DP**, or FT in ita.)



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Available information

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In order to prepare our data for the WGR on costs, we applied some **data cleaning**, **data trasformation** and **variable selection**:

- **patients' socio-demographics**: *gender* (M, F), *age at prevalence* (14-49, 50-74, 75-79, 80+)
- **clinical conditions**: *disease subtype* (proximal, distal), *comorbidities* (*Charlson index* = 0, 1, 2+, or not classified), *stage* (I, II, III, IV), distance from diagnosis (1-2, 2-3, 3-4, 4-8)
- **treatment practices**: *number of treatments*, *type of treatment* and *related costs*
- **geographical factor**: *cancer registry* (FI, FVG, LT, MI, NA, PA, UM, VE)

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Sample sizes

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- data were **originally collected monthly** → Sum over the 12 months to compute **annual costs**
- **analysis by healthcare service type and POC**

3 HEALTHCARE SERVICES * 3 POCs = 9 DATASETS

	initial	continuing	final
HA	2947	1739	1171
OPS	3085	14469	1598
DP	1164	3512	1186

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Data exploration

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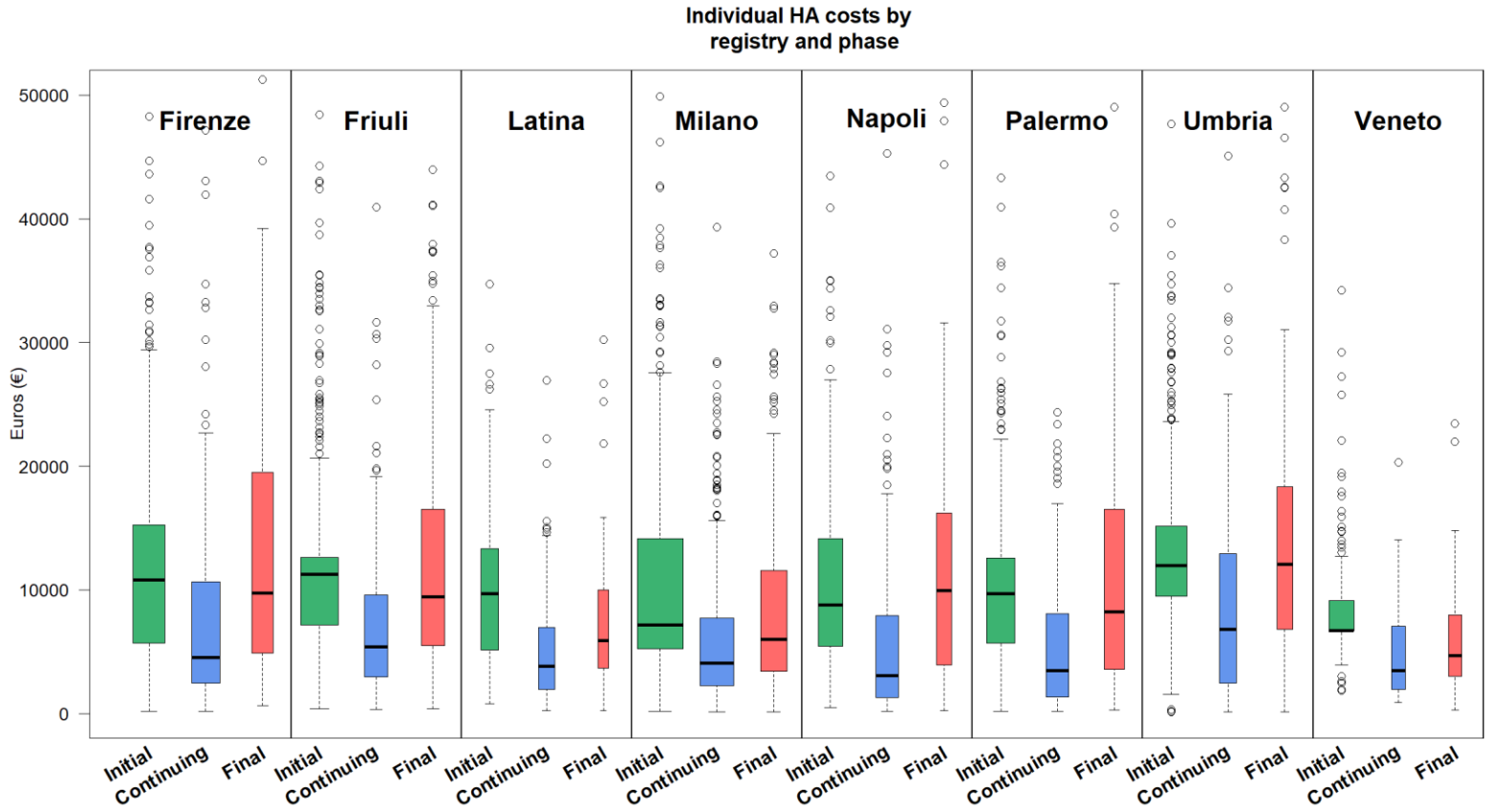

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Data exploration

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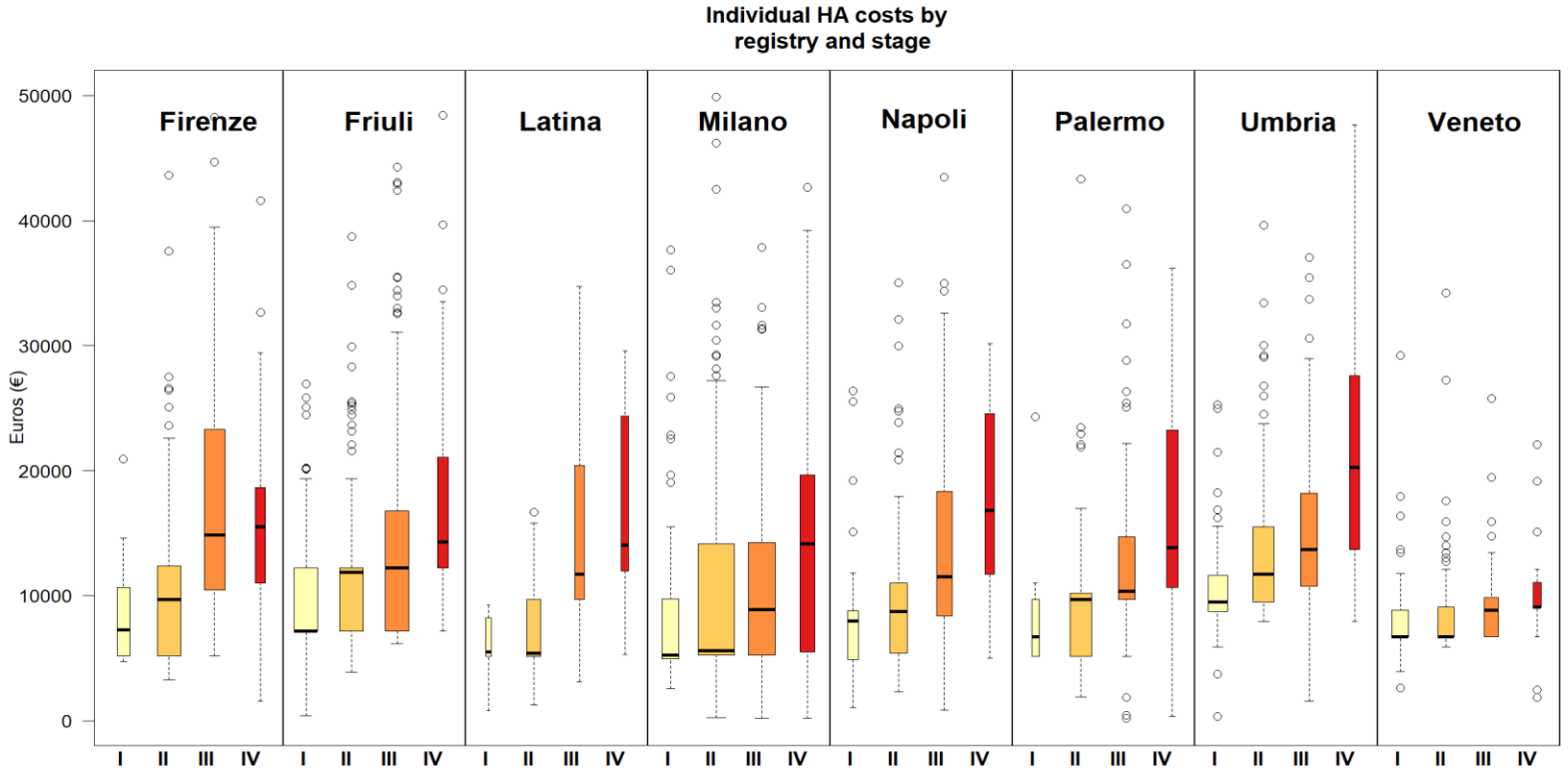

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WGR model fitting

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We implement the WGR model in the **open-source R statistical environment**:

- use of the `glmrob` function from the contributed `robustbase` package
- example of R code for HA data in initial phase

```
mod_pesi2_sdo_iniz = glmrob(costs_anno ~ sesso + eta_prev_agg1 + registro + stadio_agg + sotto_sede +
Charlson_3lv + n_tratt_anno_centr + n_tratt_anno_centr*registro, family = Gamma(link = "log"), data =
dati_sdo_anno_iniz, method = "Mqle", weights.on.x = "hat", control = glmrobMqle.control(tcc= 1.5))
```

- *method = "Mqle"* is the Huber type robust estimator
- *weights.on.x = "hat"* is the robust function specification with $w(x_i) = \sqrt{1 - H_{ii}}$ (h_{ii} element of diagonal matrix)
- *control = glmrobMqle.control(tcc=1.5)* is a tuning to handle the iterative fitting estimation process

see Cantoni and Rocchetti 2006 and R documentation for more details.

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Estimated effects

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- num. of treatments and disease stage have **always a significant positive effect** on average costs: higher num. of treatments or cancer stage increase expenses.
- age at prevalence has a **significant negative effect**: older patients are less costly.
- distance from diagnosis is similar to age at prevalence, but with a **significant negative effect** only when several years have passed from diagnosis.
- comorbidities have a **significant positive effect** on HA costs in initial phase, but a **significant negative effect** on OPS and DP costs.
- cancer subsite is **not significant.**
- cancer registries have **always significant effects**, with an associations varying for the different cost components consistently with the characteristics of the local healthcare administrations.

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Main differences with classic Gamma regression

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- **cost drivers identification**: the WGR highlighted sex as a significant predictor of OPS costs for all POCs, with females having significantly lower expenses than males, whereas the estimated effect is not significant with the GR.

- **improvement of goodness-of-fit**:

BIC values are better with the WGR than the classic GR in 7 out of 9 cases

		WGR	GR
HA	initial	**57726**	58225
	continuing	**32707**	33767
	final	**22706**	23742
OPS	initial	**49624**	50421
	continuing	202913	**202017**
	final	**24865**	25740
DP	initial	**11734**	12212
	continuing	33688	**32666**
	final	**13954**	14536

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Conclusions

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Final remarks:

- **usefulness of regression modelling** for evaluating cancer cost levels and drivers
- description of **robust estimation of Gamma regression**
- several **theoretical and practical advantages**
- **better detection of influential factors**, including meaningful territorial patterns

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Future research

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Possible **future developments**:

- application to **other cancer types**
- **additional covariates**: more specific categorization of the cancer type
- use of the weights to **characterize patients with outlying costs**
- **other robust strategies**: modelling median instead of mean costs
- development of an **R package** for modelling cost data at micro-level

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Thank you!

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