



Analysing the effects of the 2022 Italian tax-benefit reform at local level using spatial microsimulation

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The challenge (1)

- Most of empirical research on the **effects of public policies** using quantitative methods takes place at **national level**
 - **Policy-making powers** in most countries overwhelmingly rest with **national governments**
 - Design and sample size of a survey designed to ensure **statistical significance**
 - ✓ at national level
 - ✓ at NUTS-1 level (macro areas)
 - ✓ or in some cases at NUTS-2 level (IT: *Regioni*; ES: *Comunidades Autónomas*)
 - ✓ but not at the province or town level (let alone at neighbourhood level)

The challenge (2)

- **Growing importance of local level** as the focus of analysis
 - Effects of the same **macroeconomic shock** typically **vary by locality**, changing the geography of prosperity, employment, poverty, inequality etc.
 - **Devolution of tax-benefit policies** from central to local (i.e. regional or municipal) authorities (see Gori 2023 “Il reddito minimo in azione”)
 - **Spatial inequalities** occasionally erupt on the national scene: Brexit / Trump / *Gilets jaunes* (see Rodríguez-Pose’s 2018 paper “The revenge of the places that don’t matter”)

The challenge (3)

- To make quantitative methods more ‘granular’, enabling analysis at small-area level, we would ideally **need a dataset** that can be used both:
 - to **explore spatial variation in living conditions**
and
 - to monitor the effects of changes in **tax-benefit policies**
- Such a dataset does not currently exist (at least in Italy!)

Solutions (1)

- What are the remedies?
- A solution would be to **increase the sample size of survey data** to ensure statistical significance at NUTS-3 level (in IT, ES: provinces), or conceivably even lower
- Disadvantages:
 - **Prohibitive cost**
 - For example, EU-SILC already now enables analysis at NUTS-2 level only in some countries (IT, ES)

Solutions (2)

- **Registry data** could well be the future: high accuracy, granular at the local level, large number of observations (big data)
- Disadvantages:
 - **Tax returns data not enough:** limited coverage of some vulnerable populations (e.g. non-tax payers)
 - **Privacy concerns**
 - Limited access

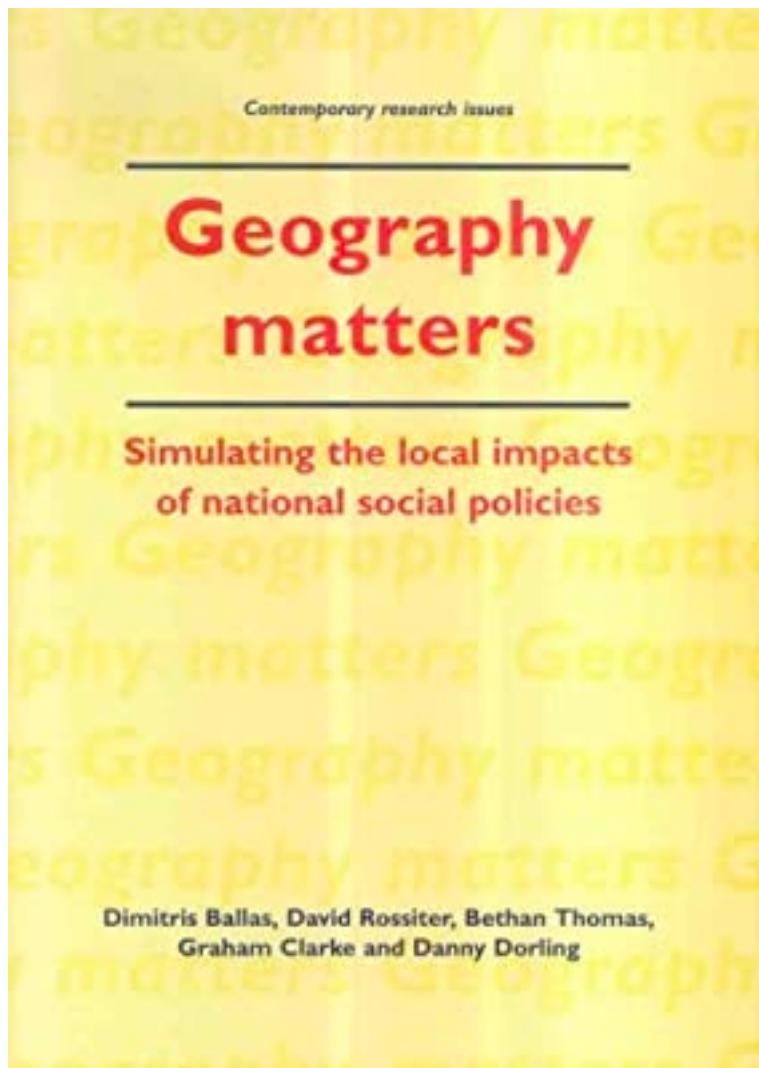
Solutions (3)

- **Small area estimation:** impute into population census data an outcome variable (e.g. equivalised disposable income; poverty status) from household survey data—which has a sample too small for small area disaggregation
 - World Bank method based on regressions (Elbers et al. 2003)
 - M-quantile approach (Chambers and Tzavidis 2006; Giusti et al.)
 - Empirical Best Prediction approach (Molina and Rao, 2010)
- However, to analyse the effects of specific policies **we need the multiple outcomes** of a tax-benefit microsimulation model related to small areas
 - Need to retrieve the whole information set from surveys

Solutions (4)

- Spatial microsimulation is the fourth option
 - Create a **synthetic dataset**
 - ... in order to augment the local granularity of the income survey routinely used for distribution analysis
 - ... by drawing on publicly-available information (e.g. cross-tabulations) on the characteristics of the local communities of interest
 - Geographers have been using this approach for over twenty years
 - ✓ *Ballas D. (2001) A spatial microsimulation approach to local labour market policy analysis. PhD thesis, School of Geography, University of Leeds.*

SimBritain (1)



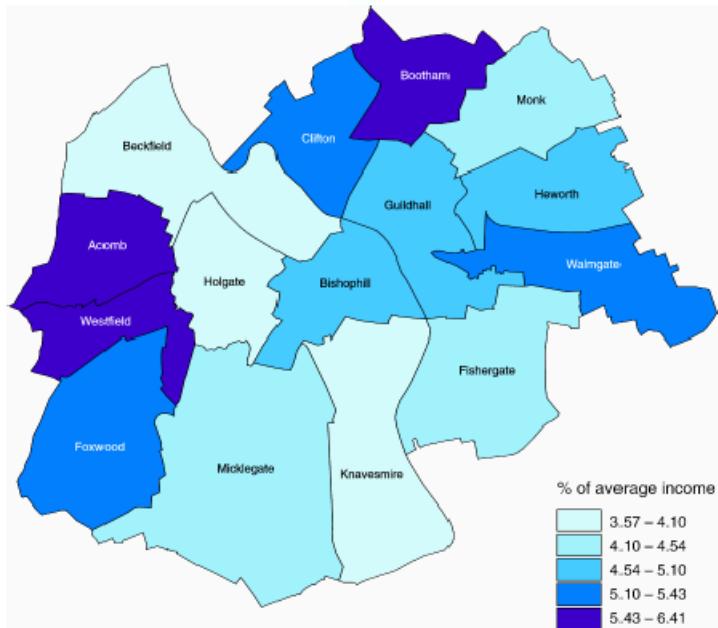
- Early example of spatial microsimulation: *SimBritain* was produced by combining the Census small-area population data with the British Household Panel Survey (BHPS)
- Joseph Rowntree Foundation report (2005)
- *"This report explores how to develop new spatial microsimulation techniques to combine census small area data with the British Household Panel Survey in order to build and update a small area population microdata set in Britain at various geographical scales between 1991-2021."*

SimBritain (2)

- *SimBritain* was adapted for local use in various settings:
 - *SimYork* (for the analysis of population dynamics in the city of York)
 - *SimLeeds* (for the analysis of the labour market in the city of Leeds)
 - *SimAlba* (for the analysis of health policy in Scotland)
 - SMILE (Ireland)
 - SimAthens (Athens)
 - ... and possibly others

SimYork

Figure 40 Spatial distribution of additional income per household as a proportion of average household income by ward, after the implementation of the April 2003 Tax Credits



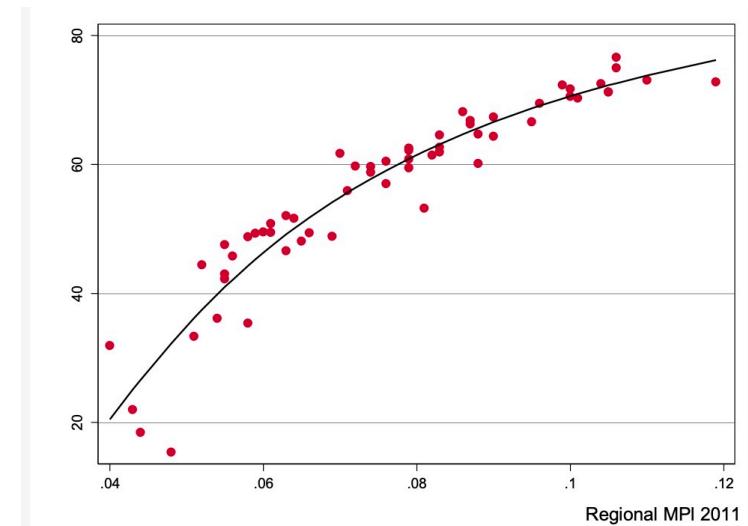
- Effects of a UK tax-benefit reform (2003)
- ... in the city of **York**
- ... by electoral **ward**
- (*average size: 5,500 individuals*)

SMILE and SimAthens

- SMILE (*Simulation Model for the Irish Local Economy*) was another such offshoot
- ✓ Ballas D., Clarke G.P. & Wiemers E. (2005) *Building a dynamic spatial microsimulation model for Ireland. Population Space and Place.*
- SimAthens based on ECHP/EU-SILC and Census data
- ✓ Panori A., Ballas D. & Psycharis Y. (2016) *SimAthens: A spatial microsimulation approach to the estimation and analysis of small area income distributions and poverty rates in the city of Athens. Computers, Environment and Urban Systems.*

“The revenge of the places that don’t matter” Greek-style

Multiple Poverty Index value in 2011 vs. share of “No” vote at the 2015 referendum by municipality in Greater Athens



EUROMODspatial Italy

- *EUROMODspatial Italy* is the latest addition
- The model
 - ... is based on **EUROMOD** to simulate the **2022 tax-benefit reform**
 - ... uses **cross-tabs from the Census and income tax returns**
 - ... to **reweight the 2019 IT-SILC dataset EUROMOD**
 - ... so it is **representative at NUTS-3 level** (107 Italian provinces)

EUROMOD

- A static multi-country tax-benefit microsimulation for the EU (Sutherland and Figari, 2013)
- 27 countries [+ UK] (mainly) using the EU-SILC as input data
- Yearly update (policy and data, up to very recent policy system)
- Simulation of
 - Income taxes, employee and employer SICs, benefits that depend on current income and observed characteristics
 - Plus unemployment benefits, with assumptions
 - Remaining benefits (e.g. contributory pensions, disability benefits) taken from input data and updated to policy year where necessary
 - (non cash income and indirect taxes for selected countries)
- Free for research purposes subject to obtaining microdata access permission (European Commission JRC Seville and Eurostat)

Italy's 107 provinces

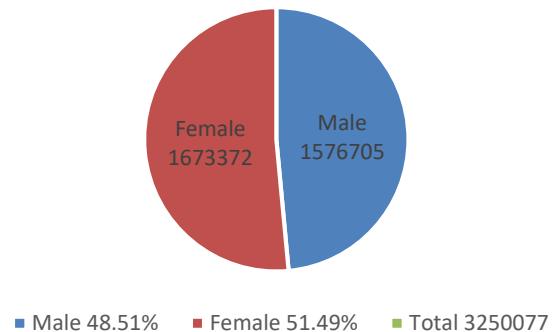


Spatial constraint variables

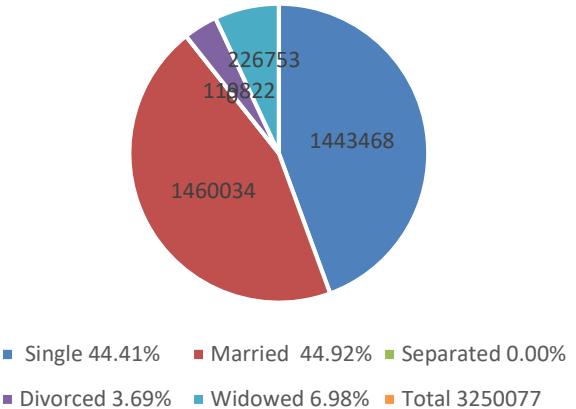
- Spatial constraint variables at *individual* level
 - from the Census:
 - ✓ gender (2)
 - ✓ age (17)
 - ✓ marital status (4)
 - ✓ education (5)
 - ✓ main economic activity (5)
 - from tax return data:
 - ✓ number of taxpayers by income class (8)
- Spatial constraint variables at *household* level
 - from the Census:
 - ✓ number of components in the household (7)
 - ✓ housing tenure (3)

Spatial constraint variables - Milan

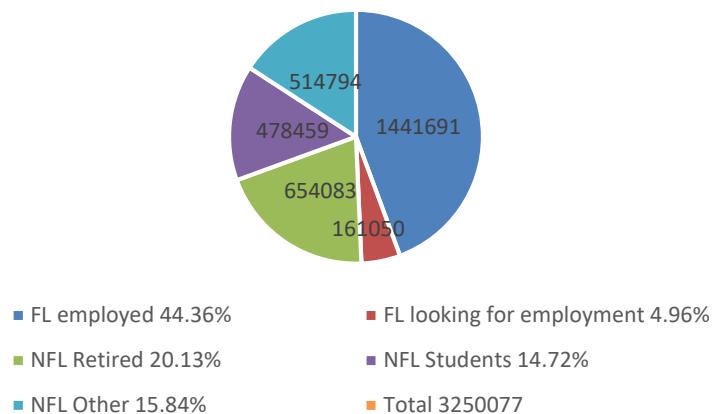
Gender distribution



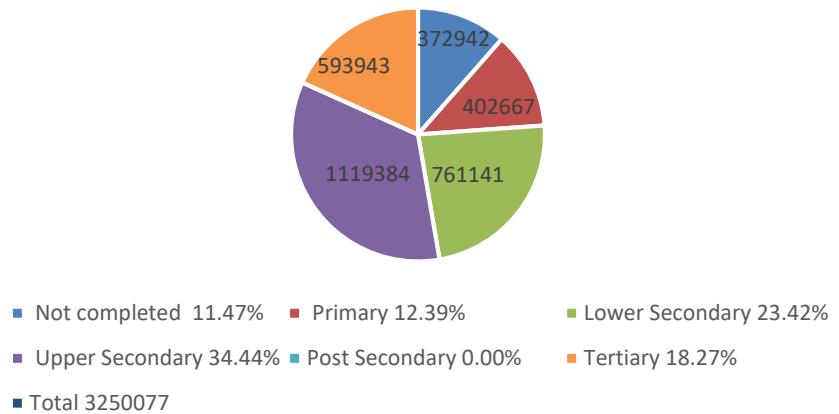
Marital Status



Occupational Status

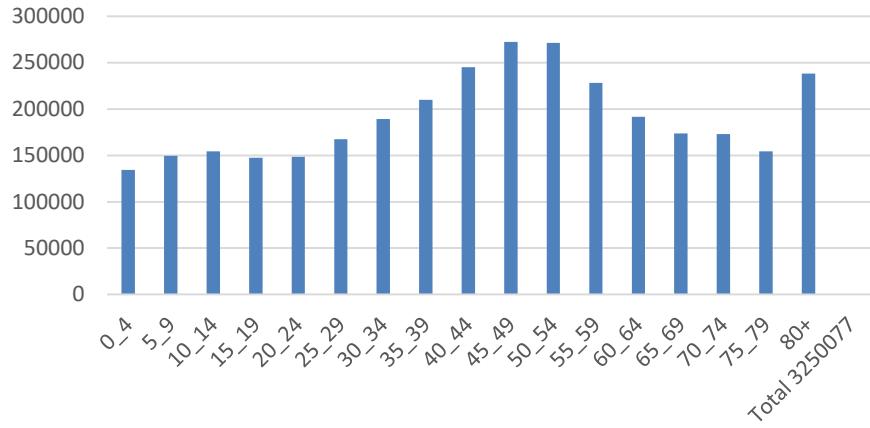


Education Status

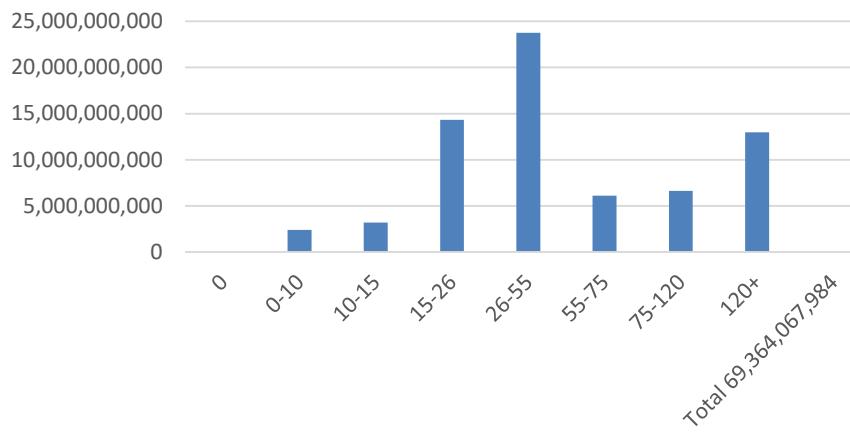


Spatial constraint variables - Milan

Age distribution

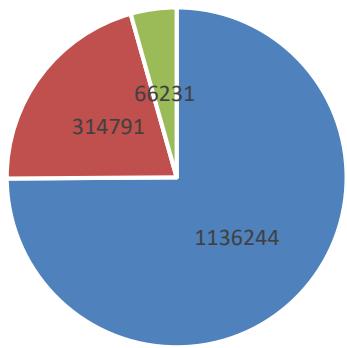


Number of taxpayers by income class



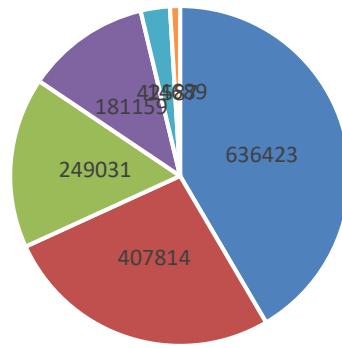
Spatial constraint variables - Milan

Housing tenure



■ Home-owner 74.89% ■ Renter 20.75% ■ Other 4.37% ■ Total 1517266

Number of members per household



■ 1 - 41.55% ■ 2 - 26.62% ■ 3 - 16.26% ■ 4 - 11.83% ■ 5 - 2.78% ■ 6+ 0.96% ■ Total 1531702

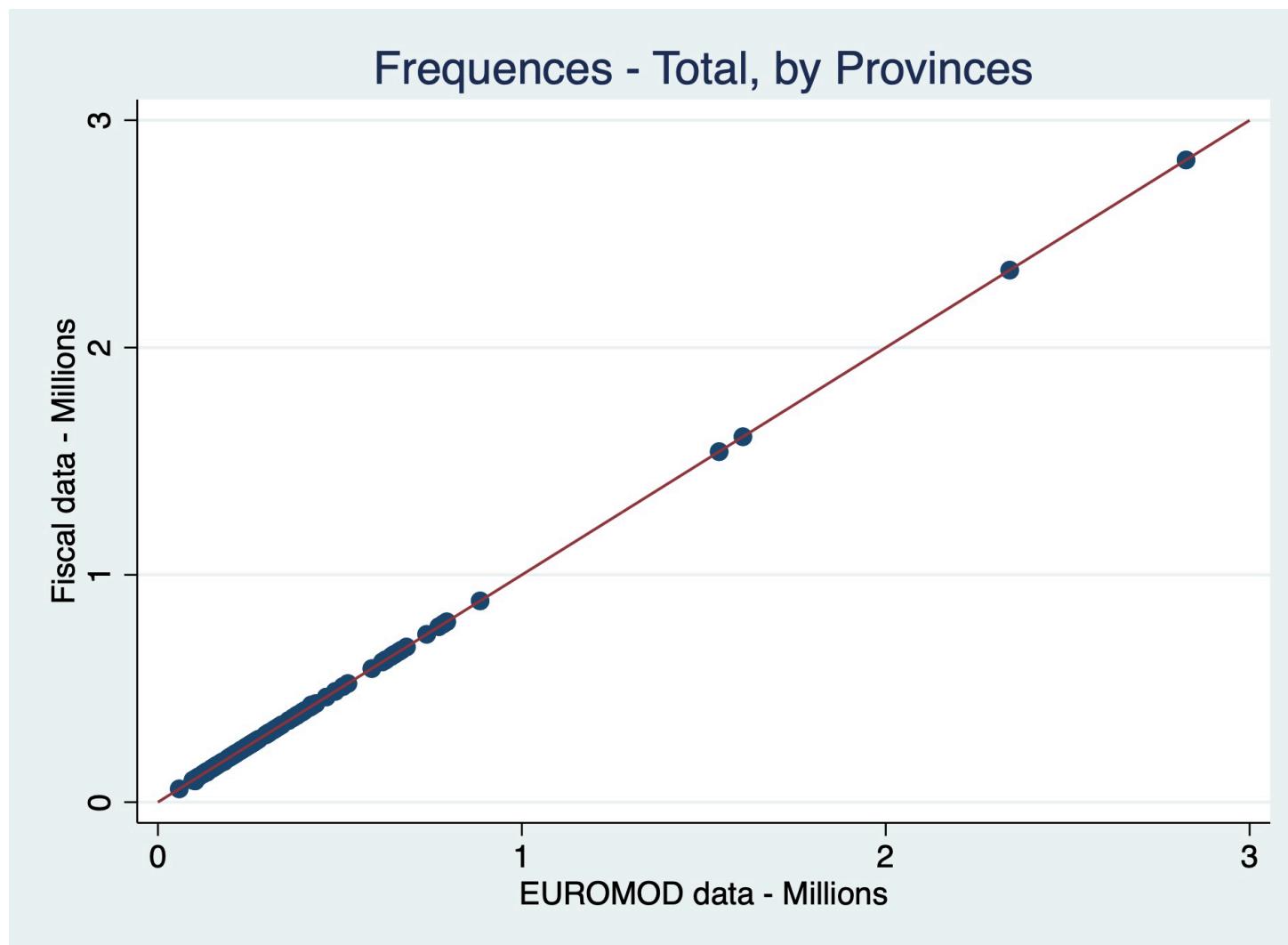
Reweighting (1)

- **Our approach**
 - ✓ For each province we start from the IT-SILC **sample** of the region (NUTS-2)
 - ✓ assign to every record a **new weight** to align the aggregates of the marginal distributions of the individual and household characteristics
 - *example: the 5,000 observations of the IT-SILC sample for Lombardy (NUTS-2) are reweighted to create 12 synthetic micro datasets – one for each of Lombardy's 12 provinces (NUTS-3)*
- **Final sample** a national level contains 277,286 observations, representative of the 107 provinces

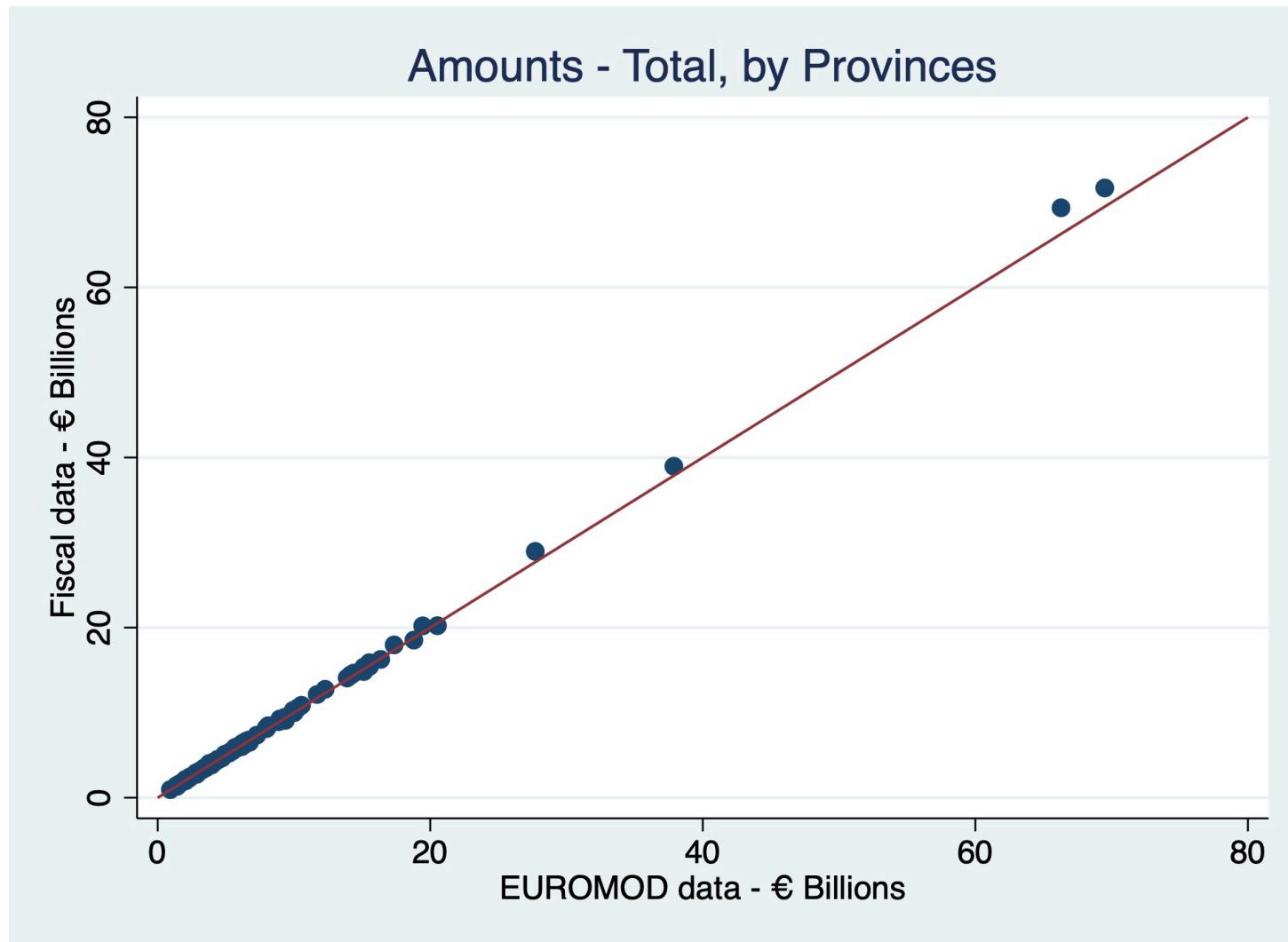
EUROMODspatial Italy (reweighting)

- Ideally, we would like to derive the new weights based on the joint distribution of individual and household characteristics
- However, this info is not publicly available in census data in a tabular format
- We had access to the micro census data at IstatLab («Adele») but latest census available refers to 2011. We use it for validation.

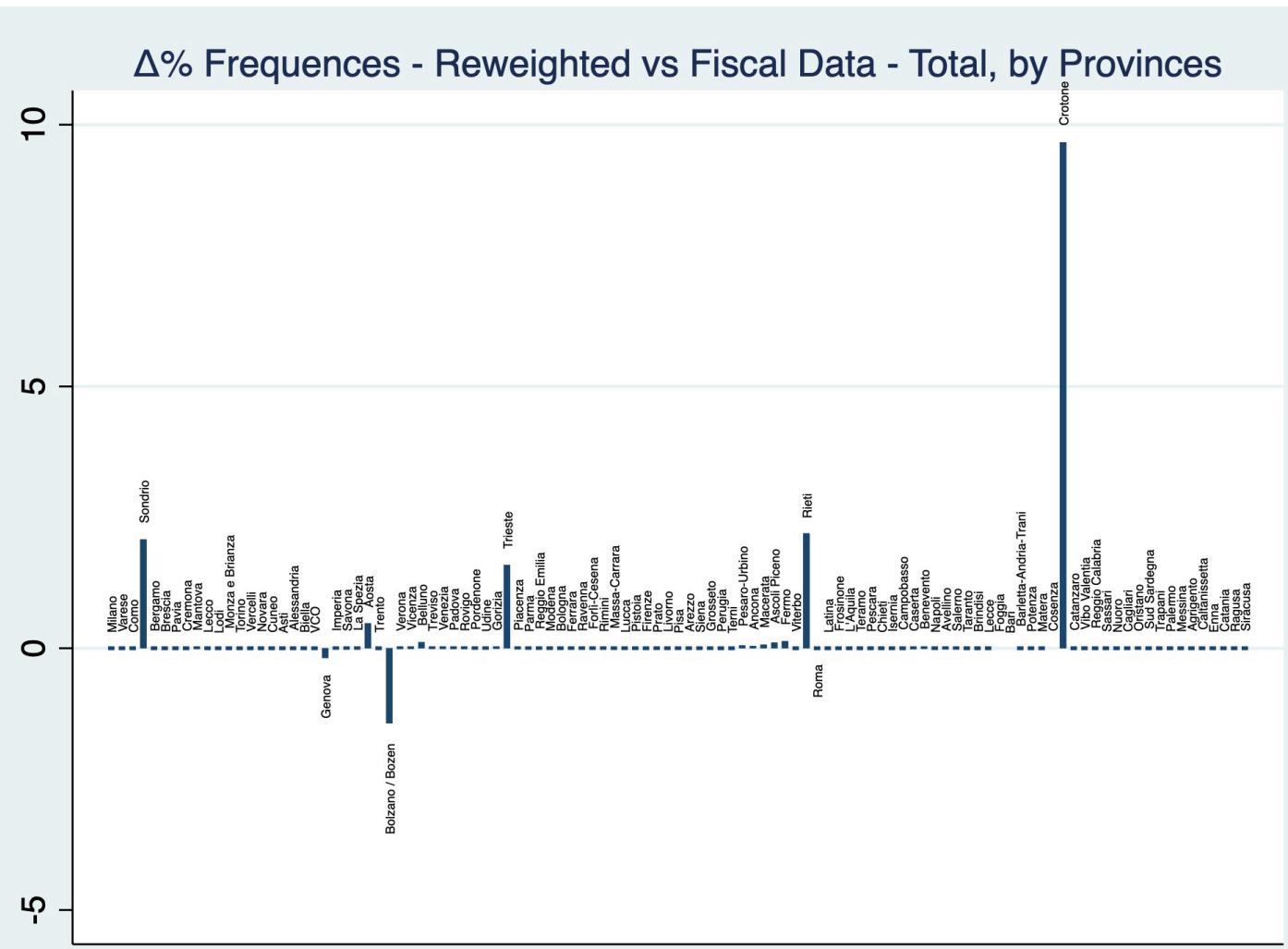
External validation 2018 – Taxable income IRPEF



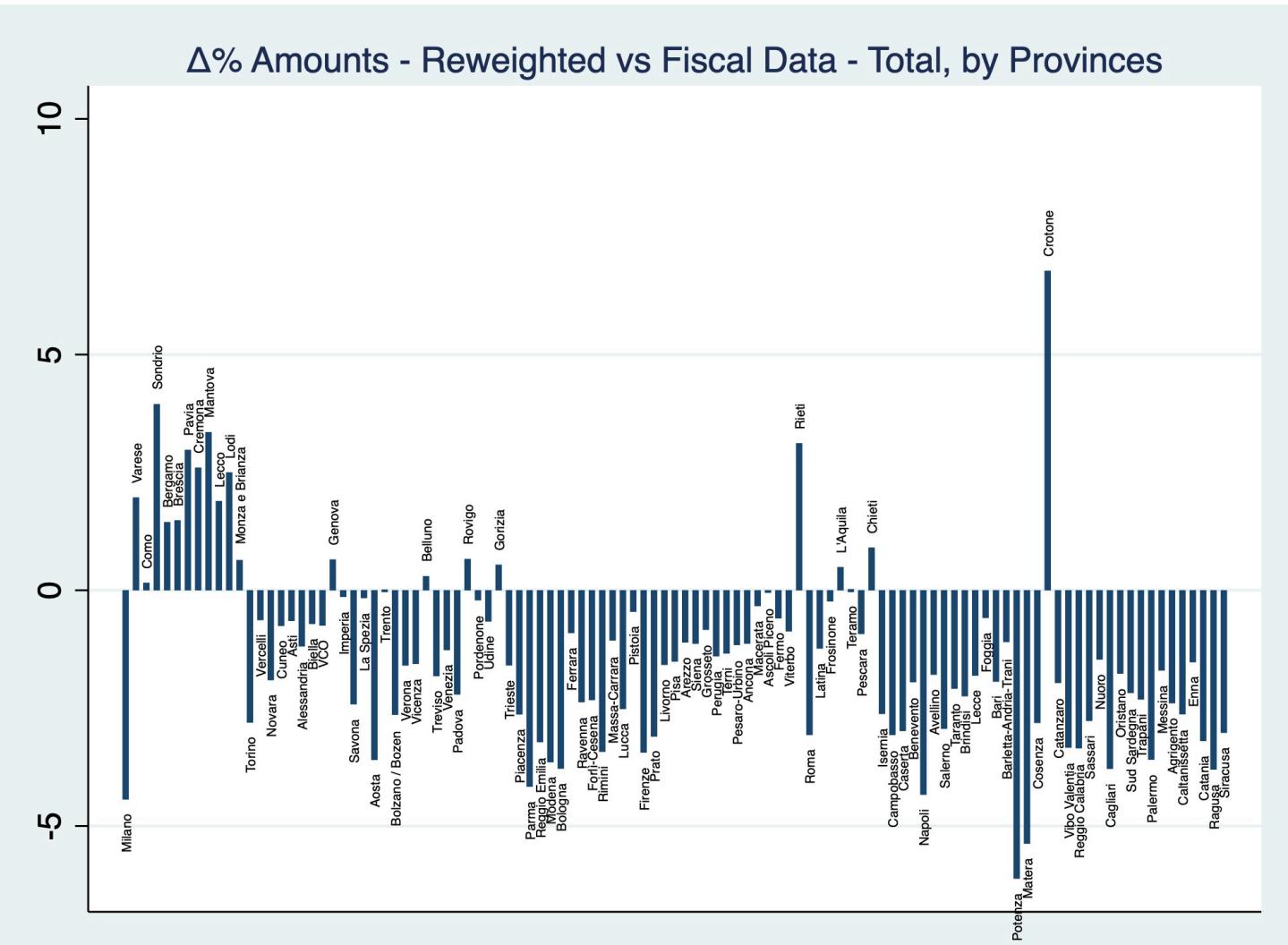
External validation 2018 – Taxable income IRPEF



External validation 2018 – Taxable income IRPEF

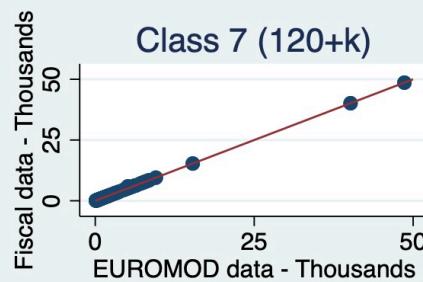
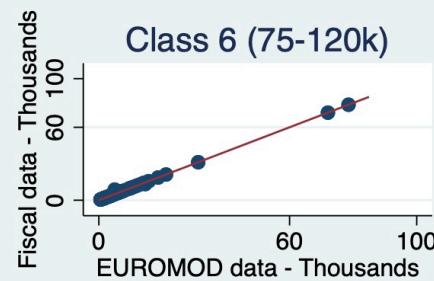
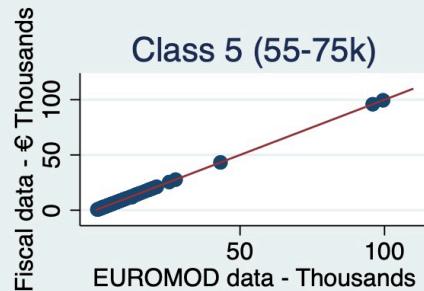
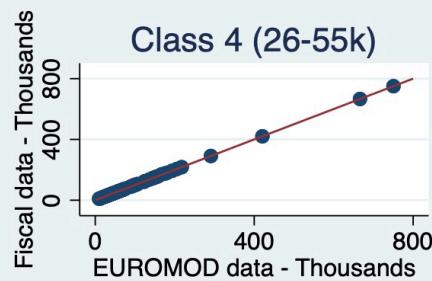
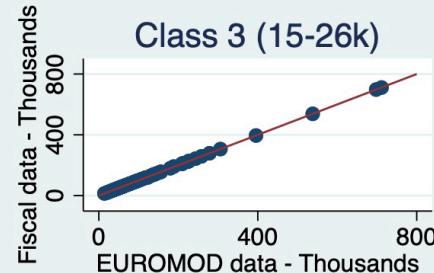
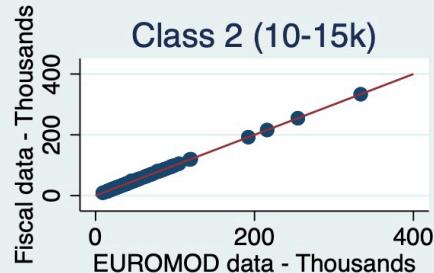
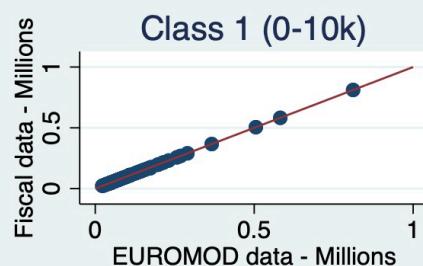


External validation 2018 – Taxable income IRPEF

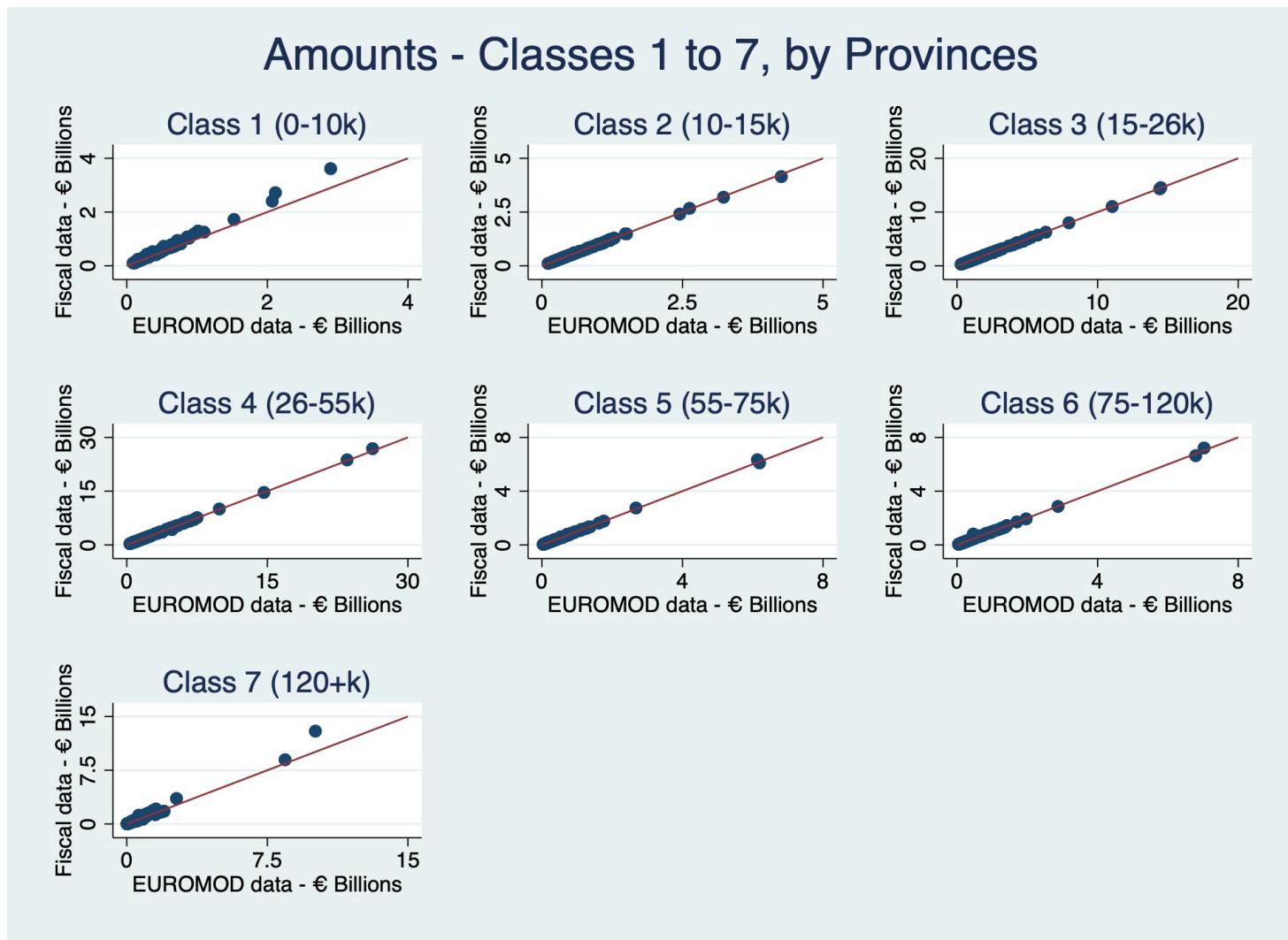


External validation 2018 – Taxable income IRPEF

Frequencies - Classes 1 to 7, by Provinces



External validation 2018 – Taxable income IRPEF



External validation 2018 – Taxable income IRPEF

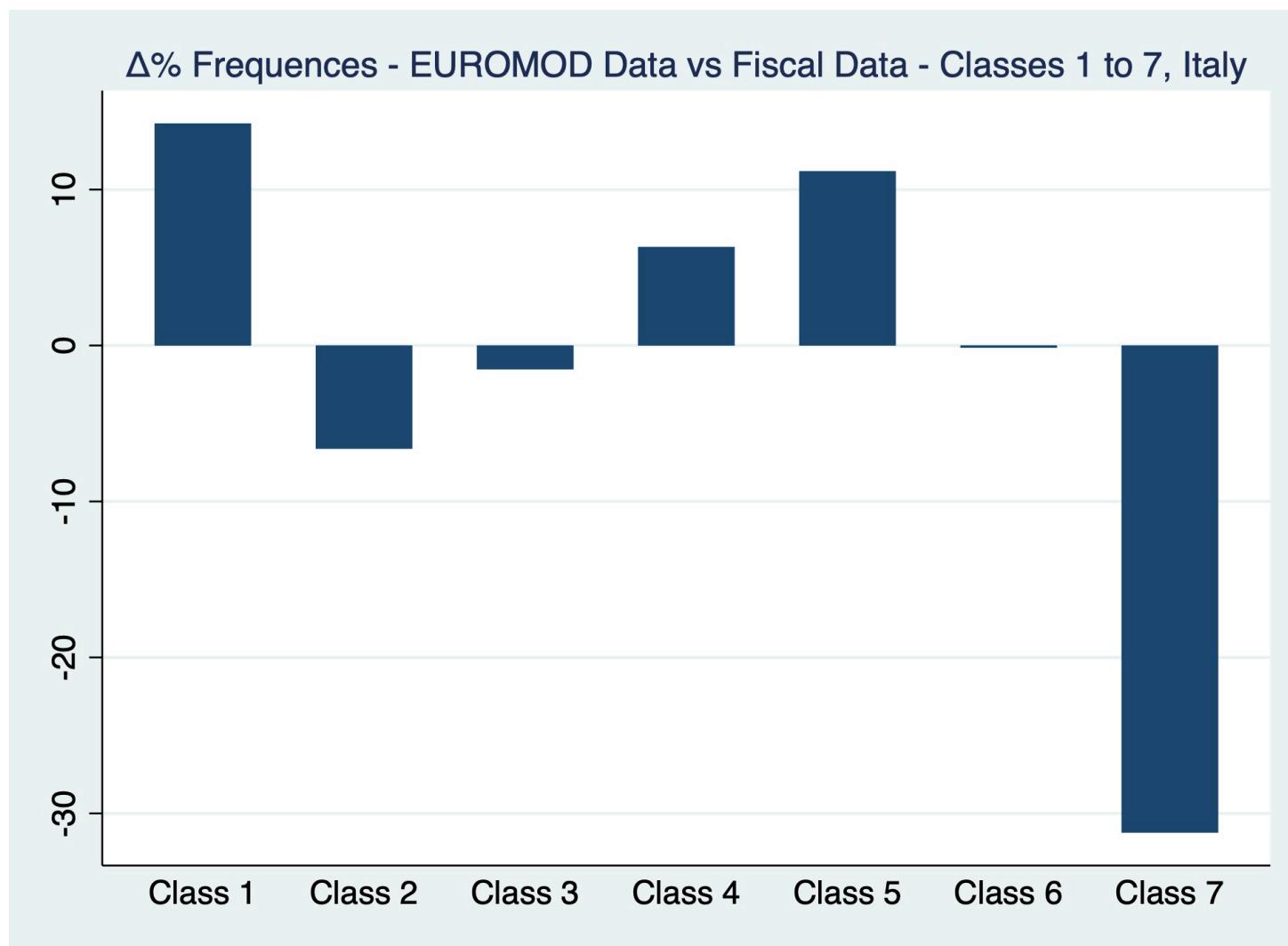


External validation 2018 – Taxable income IRPEF

Δ% Amounts Reweighted vs Fiscal Data - Classes 1 to 7, by Provinces

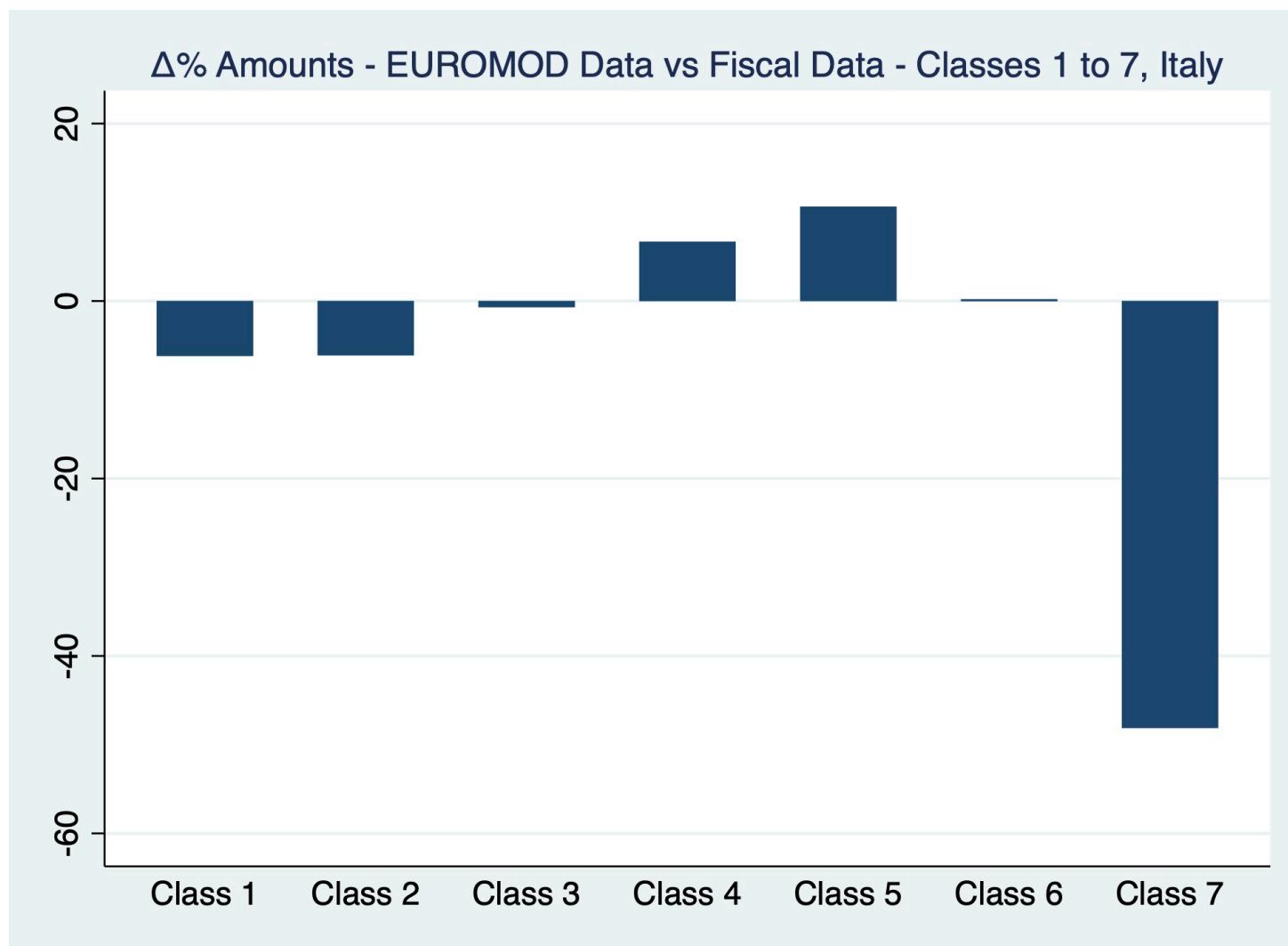


External validation 2018 – Taxable income IRPEF



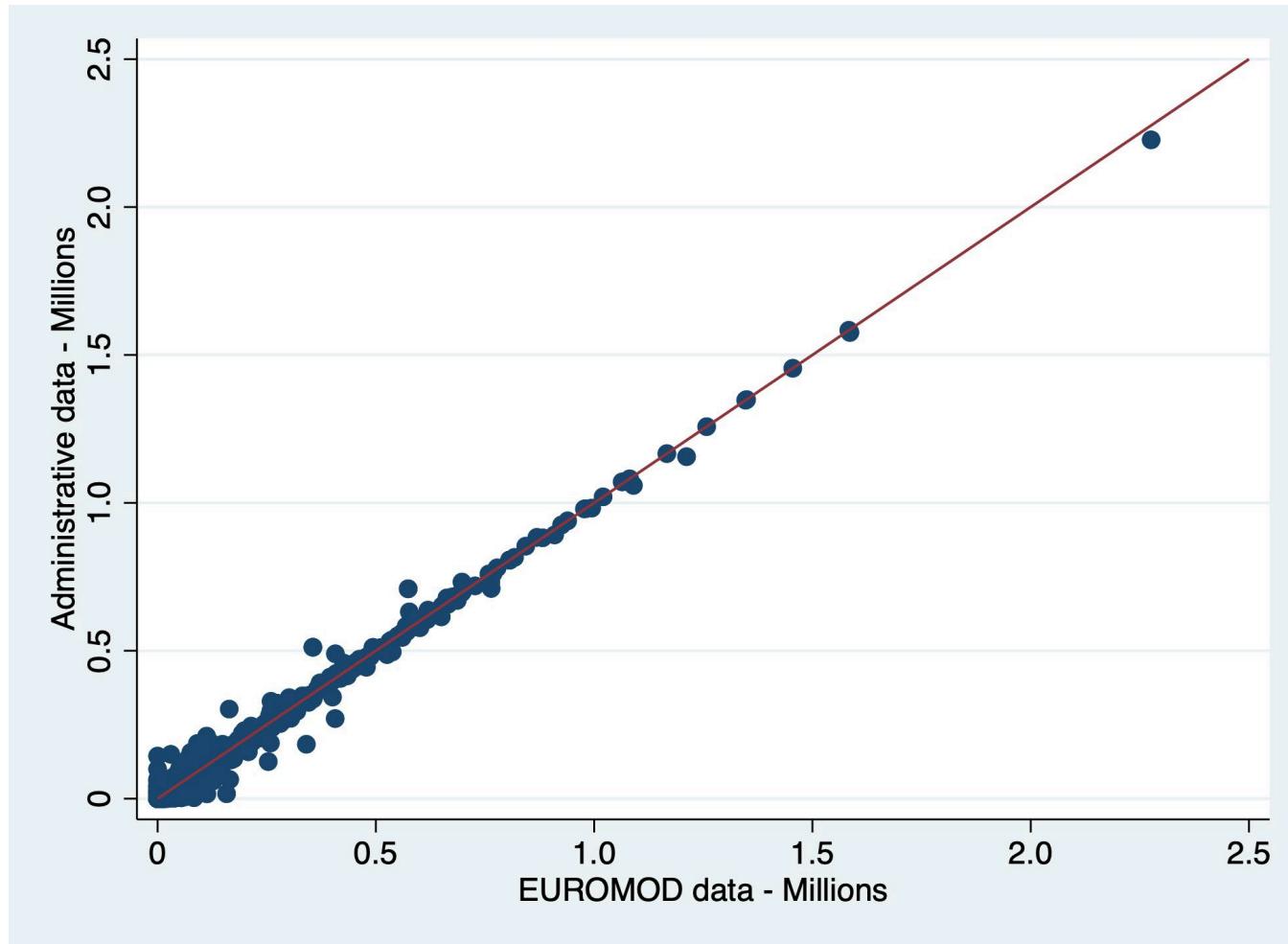
Based on original EU-SILC sample and weights

External validation 2018 – Taxable income IRPEF

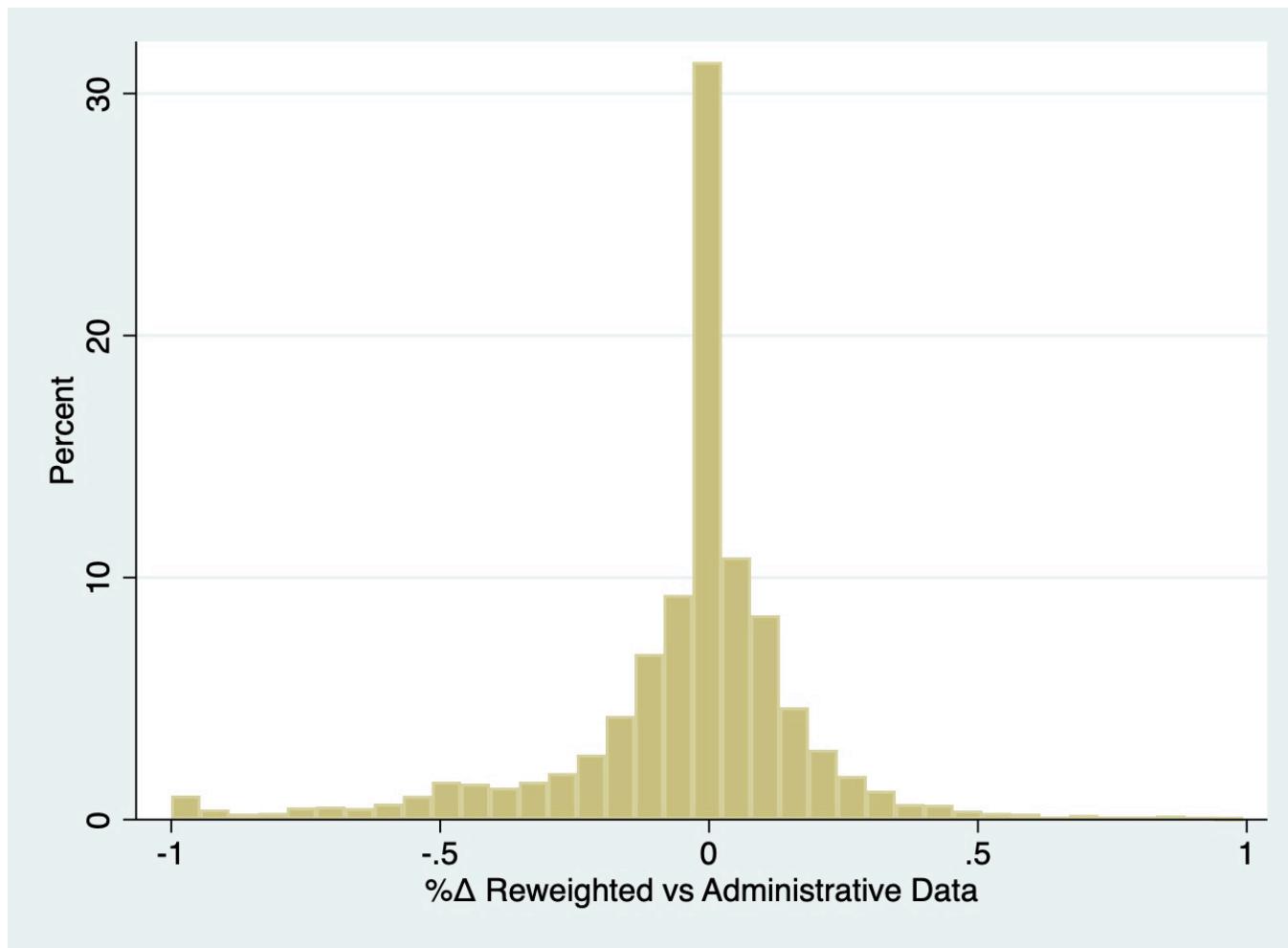


Based on original EU-SILC sample and weights

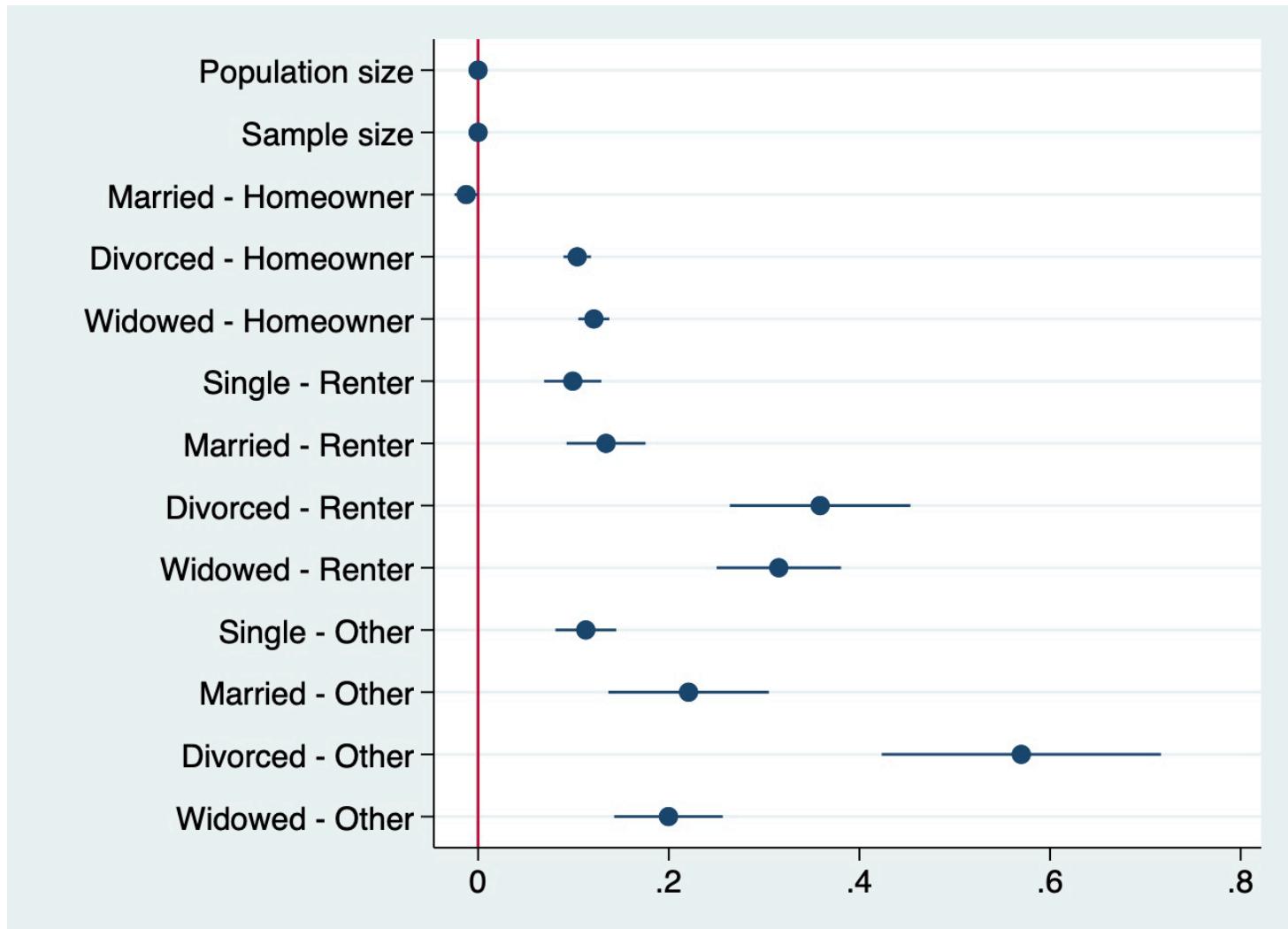
Census microdata 2011 – Frequencies



Census microdata 2011 – % Δ reweighted vs census



Census microdata 2011 – $\% \Delta$ reweighted vs census



Validation 2022 - national level

1. Fiscal

EUROMODspatial validation: income sources, 2022

	Amount (euro)				
	External source	National dataset	Ratio	Provincial dataset	Ratio
Total taxable (IRPEF) income	970,233,239,000	903,791,124,178	0.93	904,098,709,082	0.93
Net tax (IRPEF)	174,201,435,000	159,187,253,030	0.91	161,660,984,337	0.93
Net tax (IRPEF) - Regional additional	13,899,591,000	13,116,157,587	0.94	13,151,868,423	0.95
Minimum Guaranteed Income (RdC\PdC)	8,029,978,588	10,335,055,890	1.29	9,922,271,240	1.24
Family Allowance (AUU) no RdC - 10 months	13,600,000,000	12,939,946,550	0.95	13,927,040,591	1.02

Validation 2022 - national level

2. Distributional

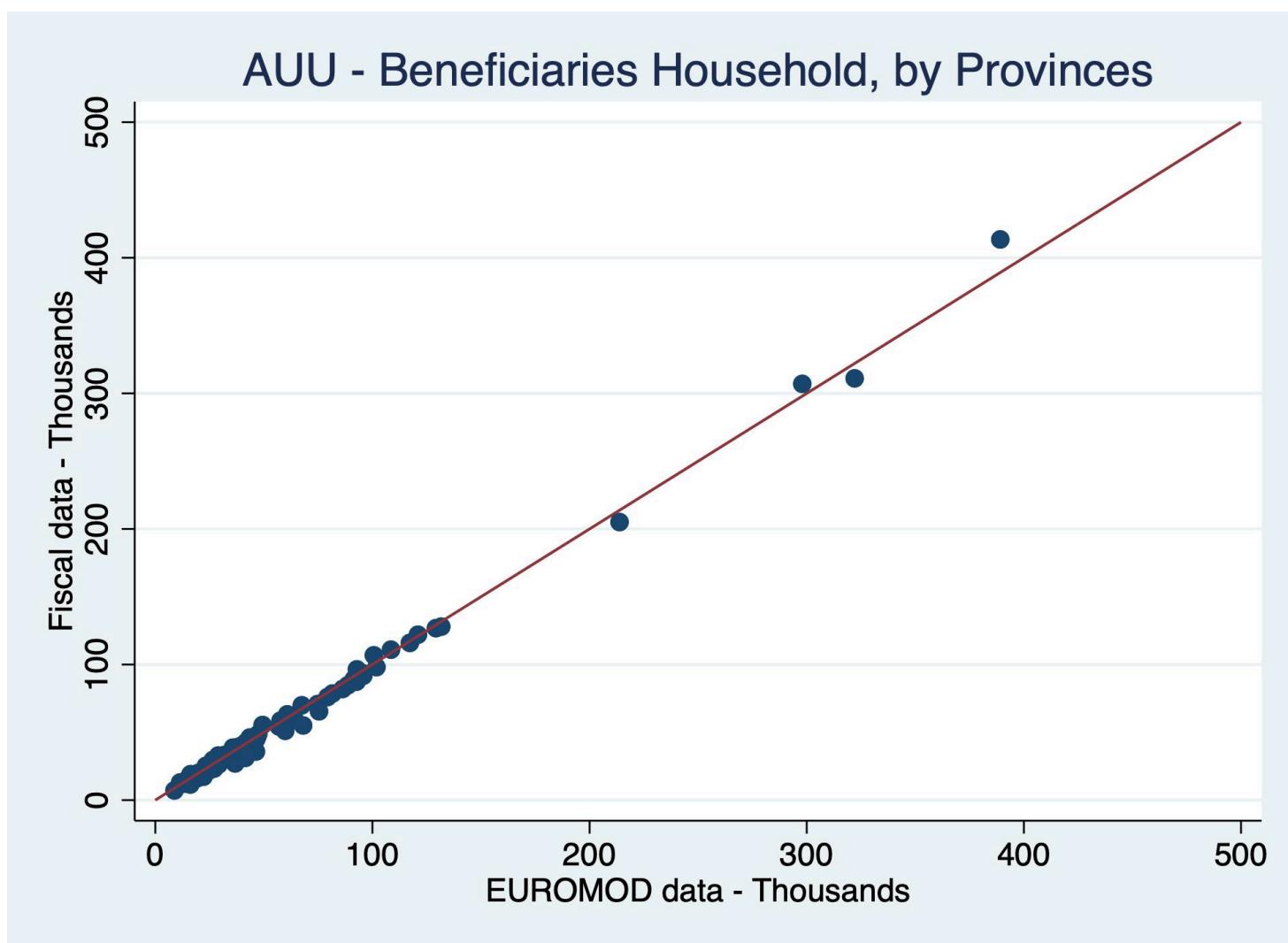
EUROMODspatial validation: poverty rates at different poverty lines, 2022

Percentage of individuals below:	National dataset	Provincial dataset	Ratio
All			
40%	0.07	0.07	1.01
50%	0.12	0.12	1.00
60%	0.20	0.20	1.01
70%	0.27	0.27	1.01
Children (<= 18)			
40%	0.07	0.06	1.08
50%	0.15	0.15	0.99
60%	0.24	0.24	0.98
70%	0.33	0.33	1.00
Elderly (>=65)			
40%	0.04	0.03	1.23
50%	0.08	0.07	1.15
60%	0.18	0.16	1.08
70%	0.25	0.25	1.02
Females			
40%	0.07	0.06	1.06
50%	0.12	0.12	1.02
60%	0.21	0.20	1.03
70%	0.28	0.27	1.03
Males			
40%	0.06	0.07	0.96
50%	0.12	0.12	0.98
60%	0.19	0.19	0.99
70%	0.26	0.26	0.99

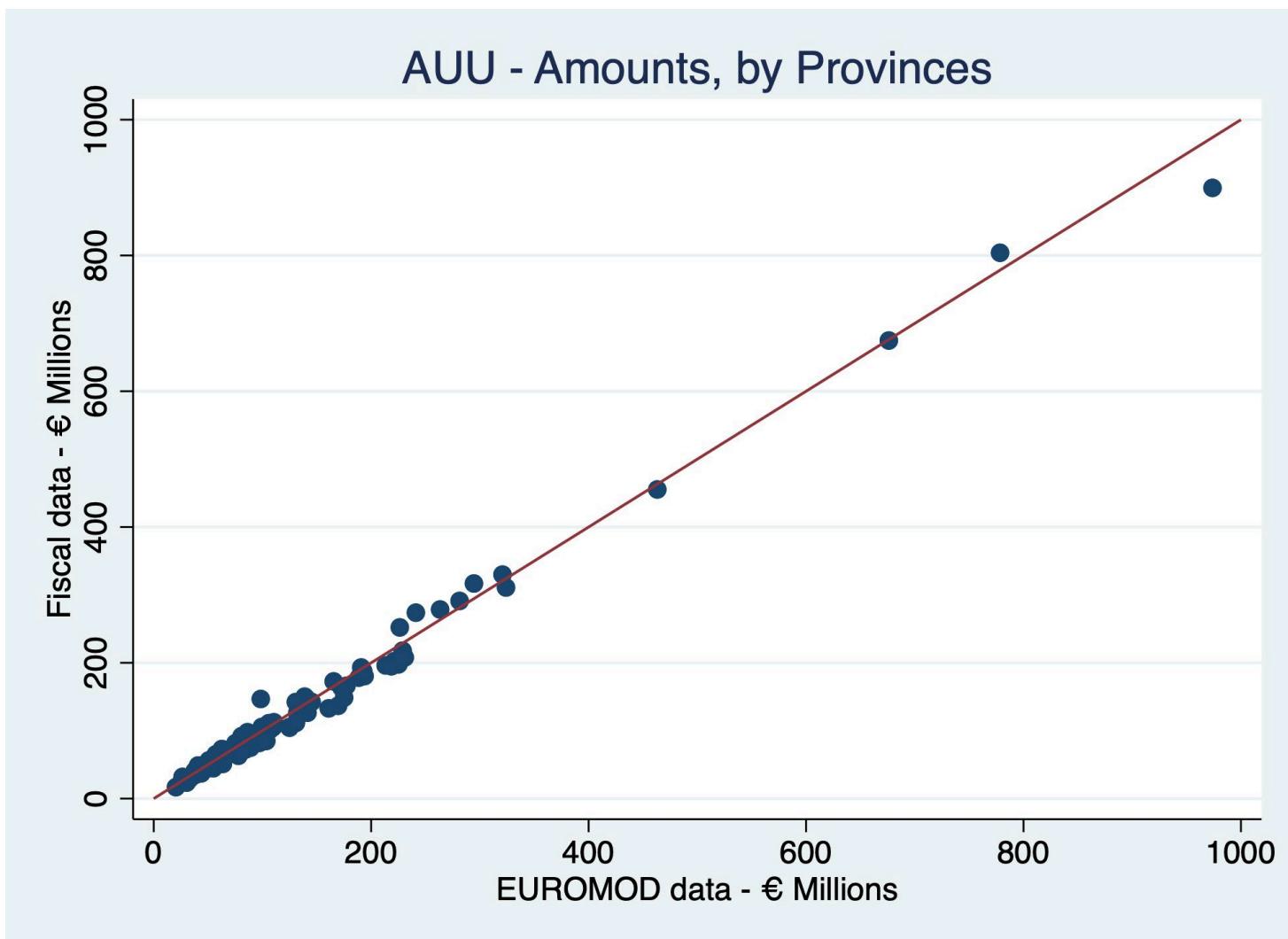
EUROMODspatial validation: income inequality, 2022

	National dataset	Provincial dataset	Ratio
Gini Coefficient Original Income	0.52	0.53	0.98
Gini Coefficient Disposable Income	0.31	0.32	0.97
Median income per decile			
1	548.26	543.73	1.01
2	815.57	807.86	1.01
3	1015.59	1014.94	1.00
4	1221.39	1215.61	1.00
5	1414.18	1407.28	1.00
6	1616.69	1607.72	1.01
7	1840.43	1819.11	1.01
8	2121.64	2105.18	1.01
9	2510.21	2517.84	1.00
10	3528.59	3511.96	1.00
Mean income (unequalised)	1189.65	1189.17	1.00
Mean income (equivalised)	1708.88	1724.45	0.99
Median income (equivalised)	1512.01	1505.77	1.00

Validation 2022 - AUU



Validation 2022 - AUU



AUU in 2022 as if paid 10 months (effective months paid: 9.3)

Research question and simulation

- Effect of the **2022 introduction of the new Family Allowance (AUU)**...
 - a. Baseline scenario
 - *2022 tax-benefit system (assuming AUU to be paid for 12 months instead of 10)*
 - b. Counterfactual scenario
 - *2022 tax-benefit system with the exception of the instruments related to children as in place in 2020 [we disregard the changes introduced in 2021 - Allowance for self-employed and supplements to the ANF]*
 - **Tax credits**
 - **Family allowances** for employees and retired (ANF) indexed as if in place in 2022 (i.e. +1.9% wrt 2021)
 - **Bonus mother, New-born bonus, Allowance for large families**
 - ... on inequality and (child) poverty at the provincial level

Social benefit reform

- Introduction of a unified child benefit
 - **(Assegno Unico e Universale - AUU)**
 - **non-categorical**: replaces contributory family allowance (*Assegno per il nucleo familiare*) only available for children of employees (incl. retired ones)
 - **universal**: all eligible for at least the minimum rate (€50 pcm per child)
 - **means-tested** supplements available (up to the maximum benefit rate of €175 pcm)

Validation

EUROMODspatial, baseline vs counterfactual, amounts

	National dataset		Provincial dataset	
	Baseline	Counterfactual	Baseline	Counterfactual
Total taxable (IRPEF) income	903,791,124,178	903,791,124,178	904,098,709,082	904,098,709,082
Net tax (IRPEF)	159,187,253,030	155,018,176,420	161,660,984,337	157,373,577,621
Net tax (IRPEF) - Regional additional	13,116,157,587	12,910,007,459	13,151,868,423	12,909,354,358
Family allowances	721,480,688	5,857,402,395	713,641,768	6,063,455,847
Minimum Guaranteed Income (RdC\PdC)	10,335,055,890	9,677,469,789	9,922,271,240	9,371,642,984
Family Allowance (AUU)	15,527,953,302	0	16,712,470,602	0
Net cost	6,674,390,959		7,383,363,998	

Results 2022 – Baseline (AUU) vs counterfactual (no AUU)

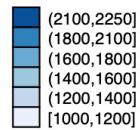
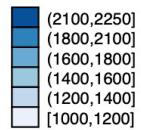
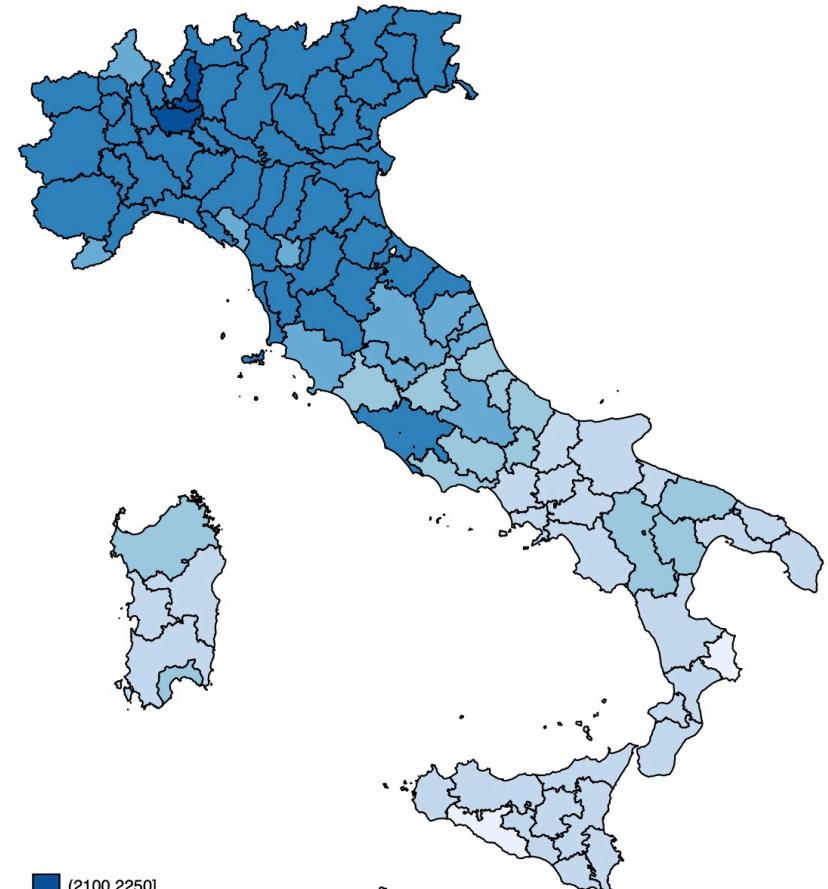
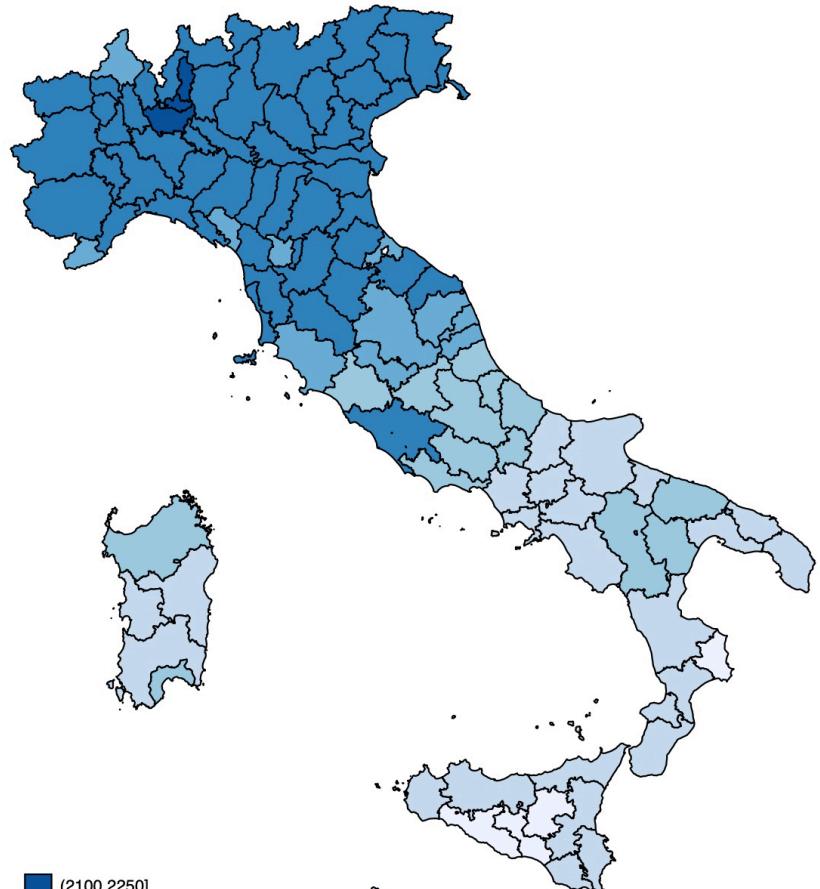
	Baseline	Counterfactual
All	19.68	20.28
Children	23.75	25.28

Fixed poverty line (60% median) in the baseline

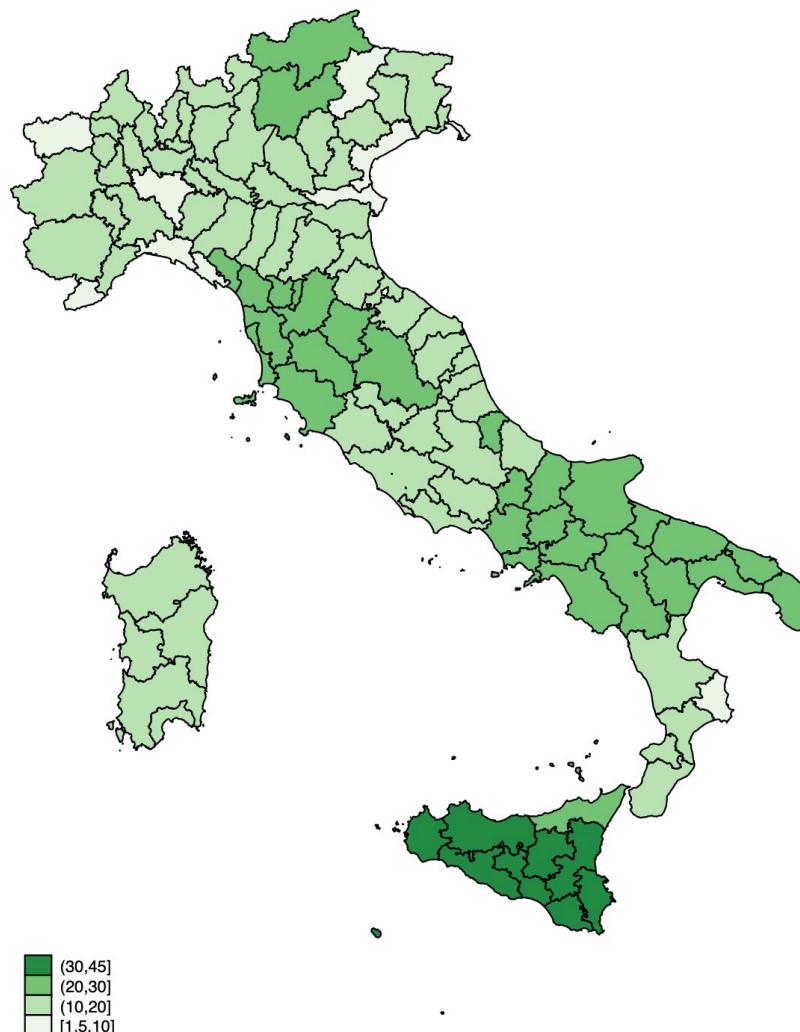
Results 2022 – Baseline (AUU) vs counterfactual (no AUU)

EUROMODspatial: income inequality, baseline vs counterfactual				
	National dataset		Provincial dataset	
	Baseline	Counterfactual	Baseline	Counterfactual
Gini Coefficient Original Income	0.52	0.52	0.53	0.53
Gini Coefficient Disposable Income	0.30	0.31	0.31	0.32
Median income per decile				
1	553.85	518.81	547.52	504.61
2	831.27	805.81	832.42	793.24
3	1028.71	1010.85	1030.06	1010.52
4	1230.37	1210.08	1225.05	1207.58
5	1423.97	1398.86	1417.65	1392.04
6	1625.60	1603.64	1614.60	1594.56
7	1846.18	1833.19	1824.61	1815.86
8	2126.99	2115.14	2108.02	2104.03
9	2513.97	2509.25	2518.09	2518.28
10	3531.56	3527.75	3520.11	3511.96
Mean income (unequivalised)	1193.73	1183.72	1193.45	1183.74
Mean income (equivalised)	1716.17	1698.53	1732.33	1714.61
Median income (equivalised)	1519.61	1502.27	1516.57	1489.29

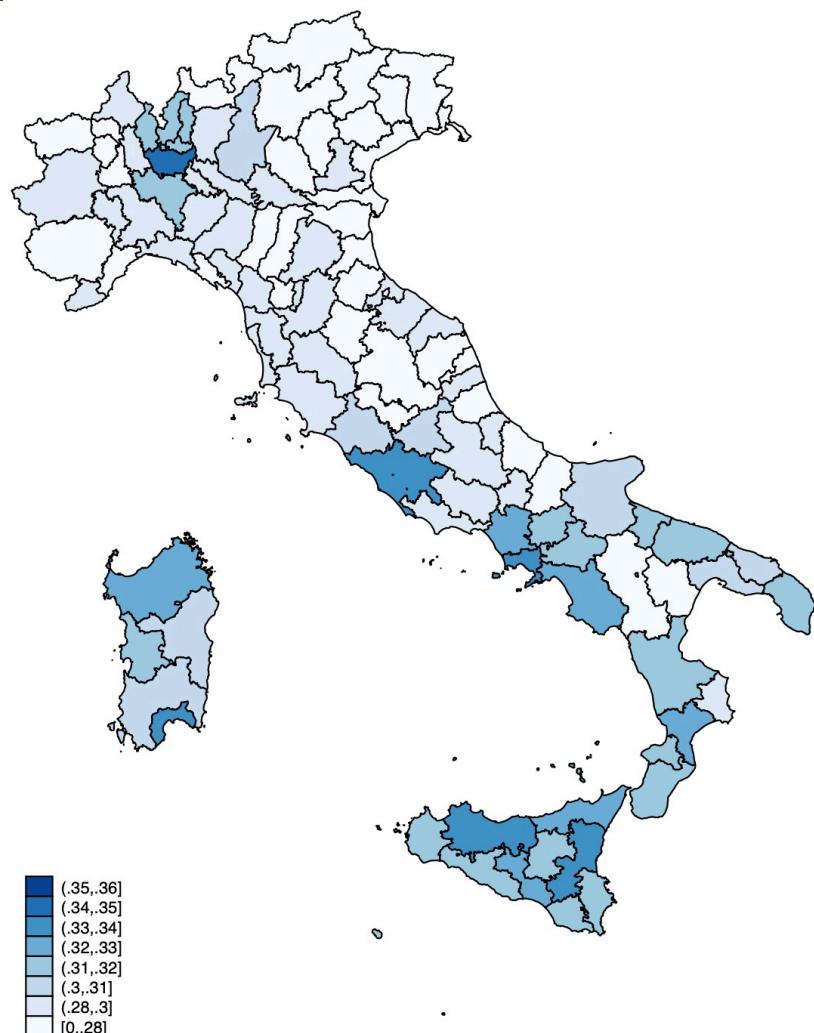
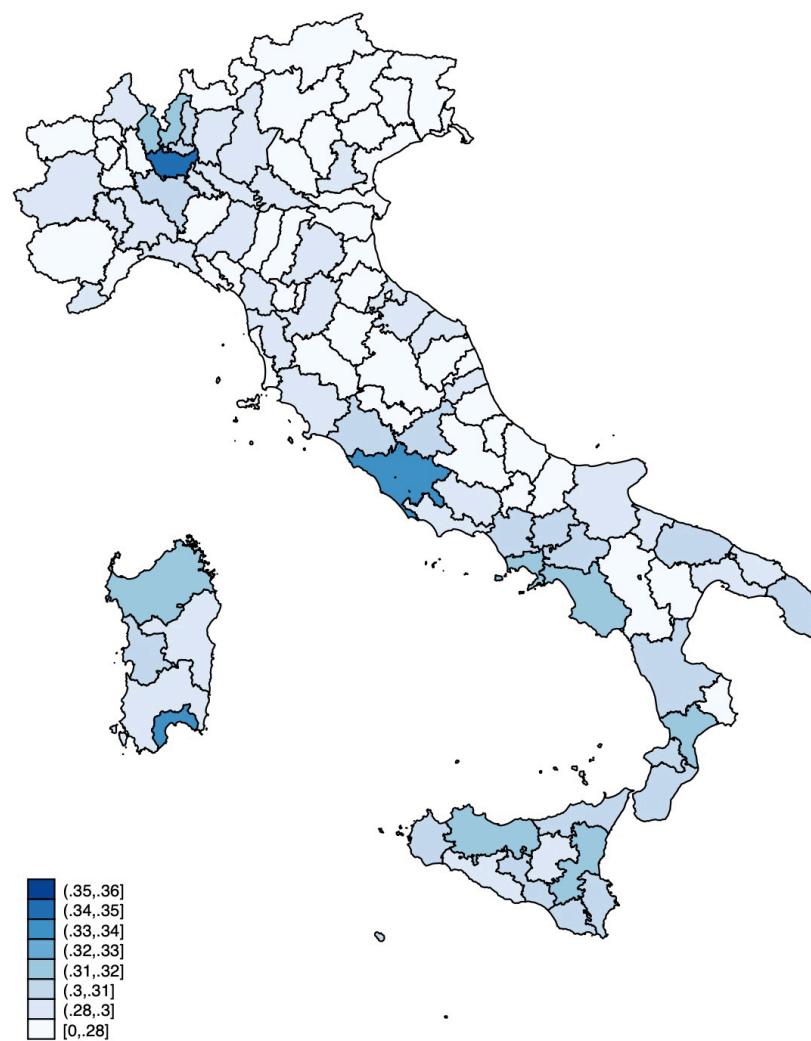
Mean Eq DPI Baseline (AUU) vs counterfactual (no AUU)



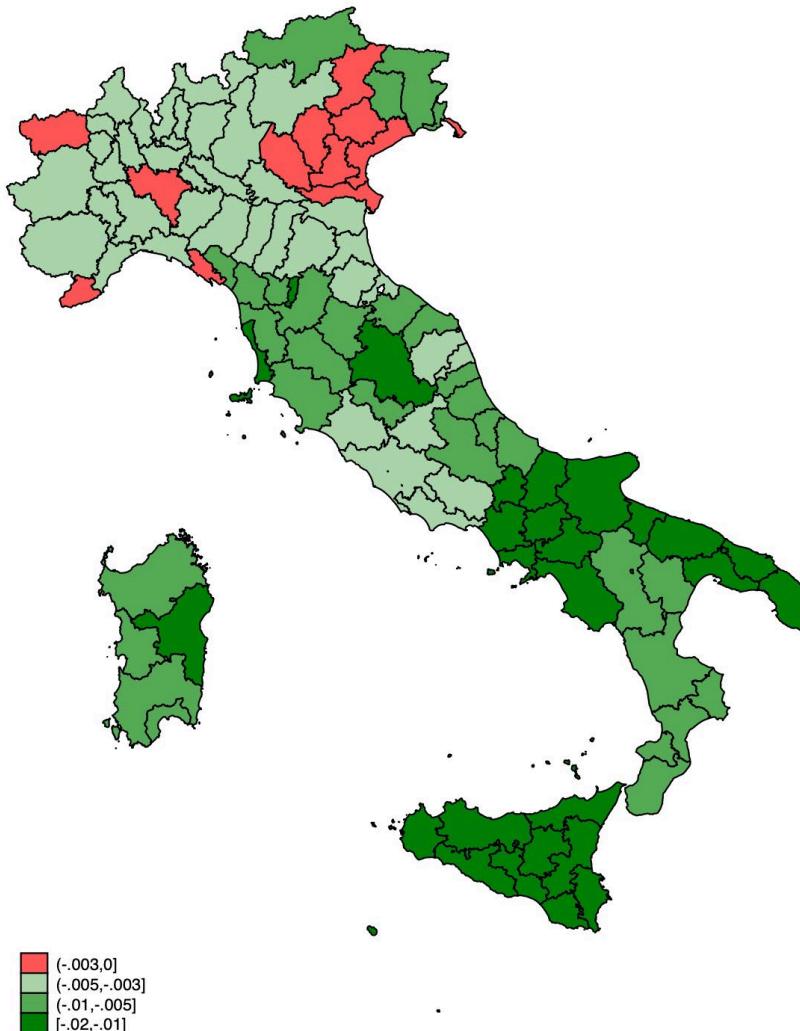
Delta Eq DPI (Baseline - Counterfactual)



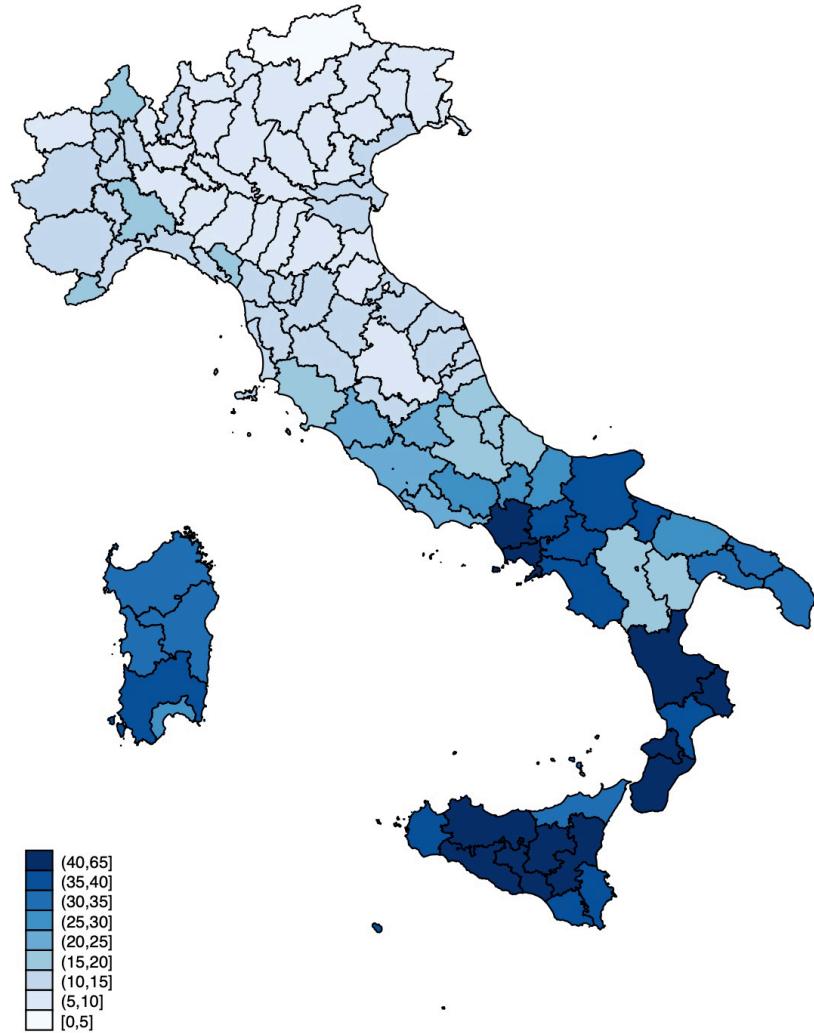
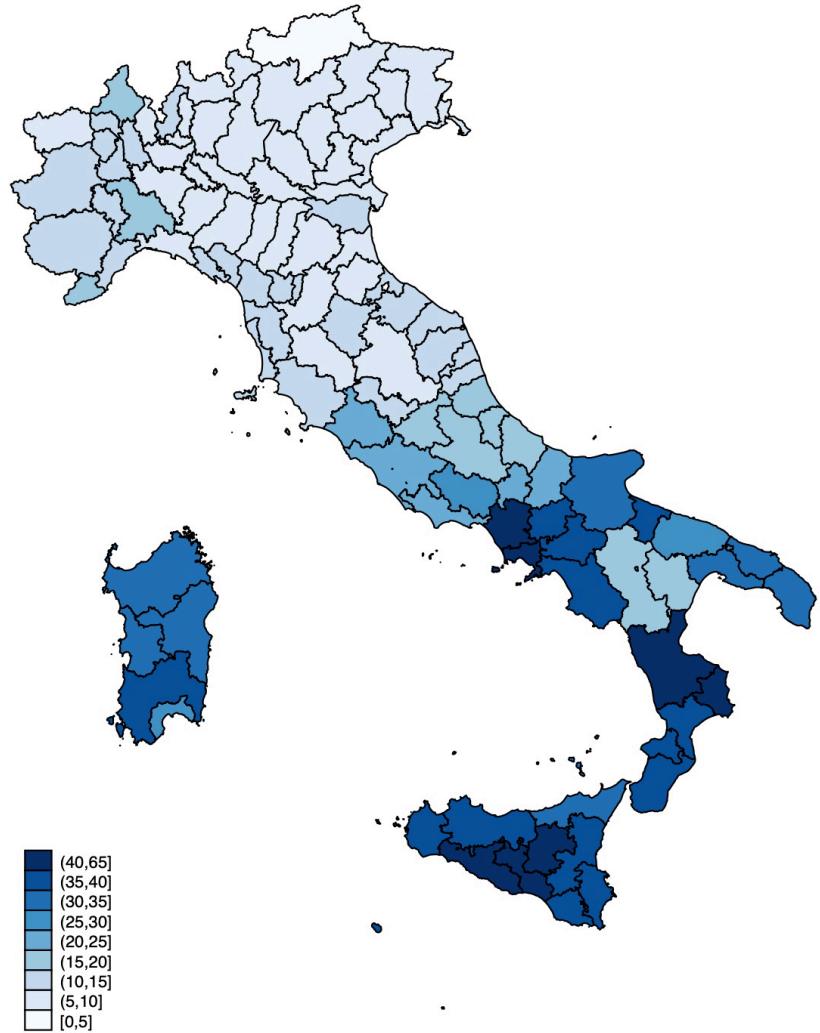
Gini - Baseline (AUU) vs counterfactual (no AUU)



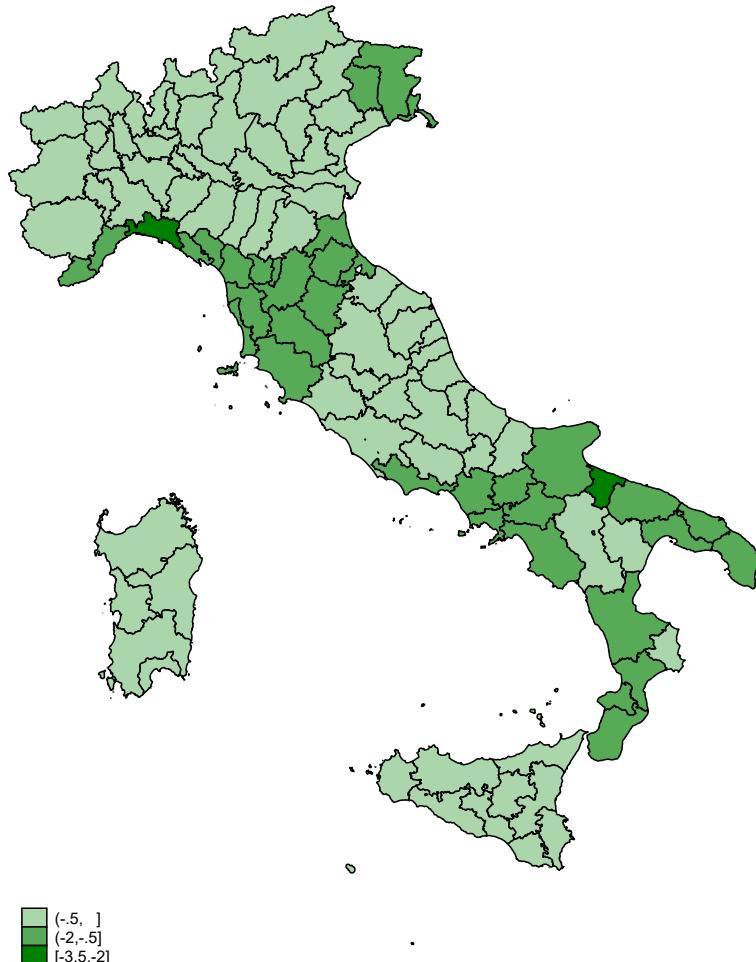
Delta Gini (Baseline - Counterfactual)



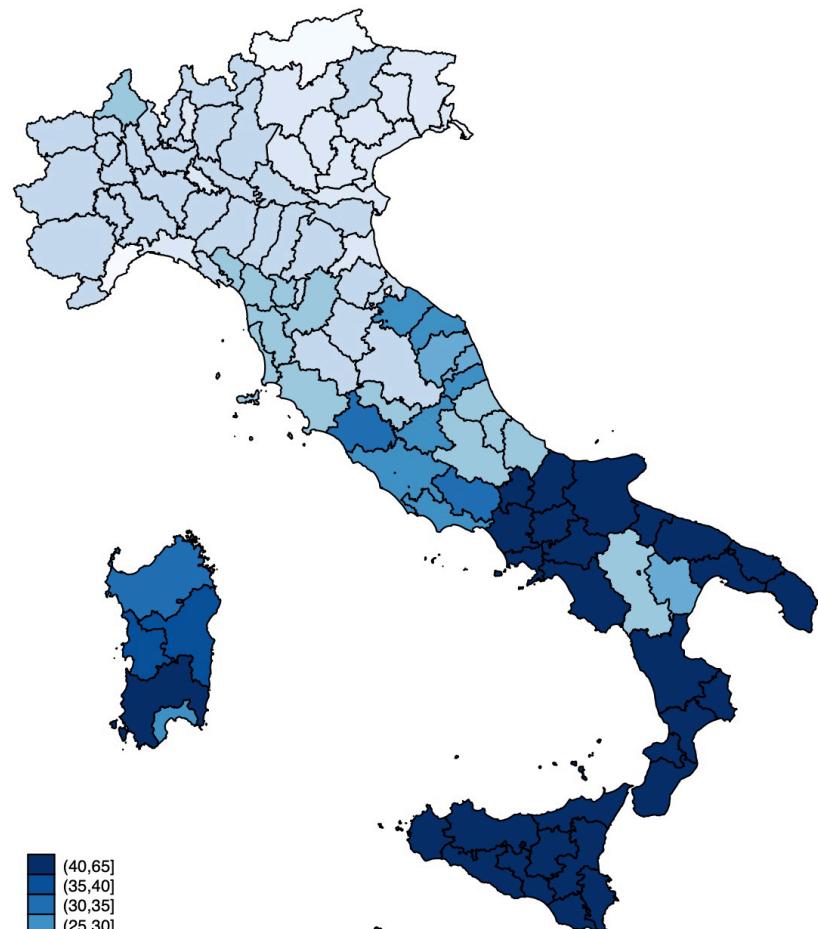
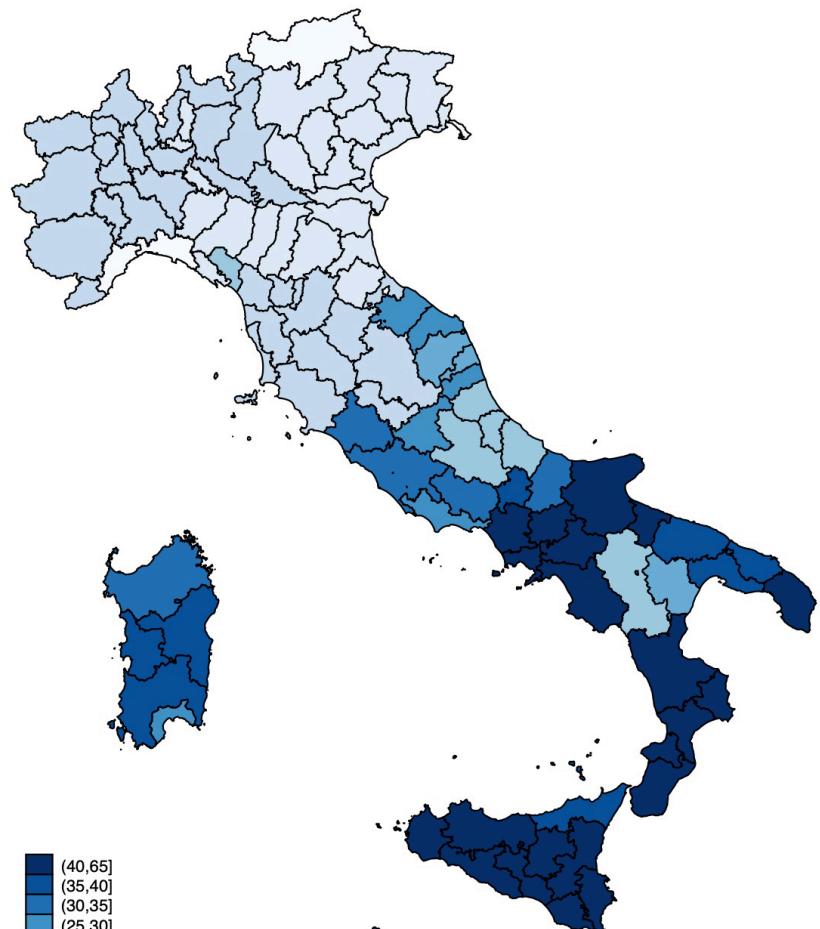
Poverty Rate - Baseline (AUU) vs counterfactual (no AUU)



Delta Poverty Rate (Baseline - Counterfactual)



Child Poverty Rate Baseline (AUU) vs counterfactual (no AUU)



Delta Child Poverty Rate (Baseline - Counterfactual)



Concluding remarks (2)

- The underlying methodology
 - ✓ has been validated (in the geography literature)
 - ✓ appears to produce plausible results
 - ✓ ... and is sufficiently honed for its application to be relatively straightforward
- However
 - ✓ Reweighting needs to consider (or at least validate) **joint distributions** of socio-economic characteristics
 - ✓ Point estimates need to be accompanied by **confidence intervals**