Local Policy Evaluation at Scale: Leveraging Survey and Administrative Data

Silvia Scarpa, Massimo Baldini, Andrea Barigazzi, Giovanni Gallo and Marcello Morciano

Abstract Policymakers increasingly demand fine-grained territorial analysis, yet survey data lack geographic detail while administrative data lack socio-economic richness. We address this dilemma through spatial microsimulation, systematically comparing deterministic and probabilistic reweighting methods to align survey weights with known population benchmarks. We construct a spatially disaggregated synthetic population for municipalities in Emilia-Romagna from the Italian EU-SILC data. Our comparative analysis highlights trade-offs between computational efficiency of deterministic methods and precision of probabilistic approaches. We demonstrate methods drawbacks and advantages to guide researchers for policy evaluation at territorial level.

Abstract *La crescente domanda di dati territoriali per la valutazione delle politiche pubbliche si scontra con un dilemma noto: i dati da indagine sono ricchi di informazioni socio-economiche ma mancano di dettagli geografici, mentre i dati amministrativi sono localizzati ma poveri di variabili. Questo lavoro affronta questo trade-off mediante tecniche di microsimulazione spaziale, confrontando sistematicamente metodi di ricalibrazione deterministica e probabilistica. Costruiamo una popolazione sintetica a livello comunale per l'Emilia-Romagna usando dati EU-SILC e vincoli amministrativi. L'analisi comparativa evidenzia i trade-off tra l'efficienza*

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computazionale dei metodi deterministici e la precisione degli approcci probabilistici, al fine di guidare policymakers nella valutazione degli interventi a livello territoriale.

Key words: Spatial microsimulation, Policy evaluation, Reweighting methods

1 Introduction

Policymakers and researchers increasingly aim to evaluate the impact of policies at the territorial level, specifically where survey and administrative data alone are insufficient to provide a complete framework. The former do not provide adequate territorial statistical representation, due to budget and time constraints; the latter cover the whole population but lack rich socio-economic variables. Spatial microsimulation (SM) methods offer a valid strategy to integrate these two sources to construct a synthetic population at the most detailed level of aggregation for which *benchmarks* are known from administrative and census data [1]. SM methods insert a spatial dimension into the microsimulation practice of evaluating policy interventions. This work offers a systematic comparison of different SM techniques, ranging from deterministic reweighting methods, namely Iterative Proportional Fitting (IPF) and the Generalized Regression Estimator (GREG), to a probabilistic approach, specifically Simulated Annealing (SA). As an illustrative case study, we employ these methods to generate a synthetic population for the residents of Emilia-Romagna municipalities, utilizing EU-SILC survey data.

2 Reweighting methods in spatial microsimulation

Reweighting methods in the SM literature aim to align the survey data S with known benchmarks X (in the form of counts) at the small area level. Deterministic procedures iteratively adjust the initial sampling weights to match these benchmarks until convergence is reached. The resulting weight may be a floating-point number, which thus requires rounding to replicate each survey individual a number of times equal to its new representativeness at the small area level. Probabilistic reweighting methods are based on sampling individuals from the survey data according to their agreement with the available benchmarks. Specifically, IPF updates each weight $w_j, j \in S$ by iteratively adjusting for each constraint $X_{d,p}$, $p = 1,\ldots,P$, independently for each area d, $d = 1\ldots,D$ [2, 4]. At step t, for individual j with characteristic $x_{j,p}$, the updated weights are computed as

$$w_{j,d}^{(t,p)} = w_{j,d}^{(t,p-1)} \frac{X_{d,p}}{\sum_{j\in S} w_{j,d}^{(t,p-1)} x_{j,p}}, \quad \forall j \in S,$$

GREG, as explained by [3], seeks to minimize a distance function (e.g., truncated chi-squared) between w_j and the new set of weights, by minimizing a Lagrangian function. Finally, Simulated Annealing (SA) is a combinatorial optimization method based on a greedy algorithm: it sets an initial temperature (typically high), swaps individuals in and out (one or more at a time), evaluates each combination according to a fitness measure, and then cools the temperature by a scale factor until it approaches zero or the error is minimized according to benchmarks [5]. This work evaluates each method using the Percentage Standardised Absolute Error, defined as $PSAE_d = \frac{1}{N_d} \sum_{p \in P} |\sum_{j \in S} w_{j,d}^{(t,p)} x_{j,p} - X_{d,p}| \times 100$, where N_d is the population size of area d.

3 Results from municipality level reconstruction

The 330 municipalities of Emilia-Romagna are heterogeneous in size, ranging from fewer than 100 to approximately 400,000 inhabitants, and characteristics, including mountain areas, towns, and cities. This work employs a selection of benchmarks such as age classes, gender, occupation status, and household size common to all municipalities and attempts to maximize the length of the X vector using a greedy algorithm. The 2022 EU-SILC dataset consists of 2,937 observations for the region and was recoded to allow for the implementation of SM methods.

Table 1 Summary statistics of PSAE by deterministic reweighting method

Method	Mean	Std. Dev.	Min	Max
GREG	1.809	4.507	0.020	56.780
IPF	3.305	7.754	0.010	101.410

As shown in Table 1, IPF displays a higher mean PSAE and substantially larger dispersion compared to GREG, suggesting lower efficiency in matching small area constraints.

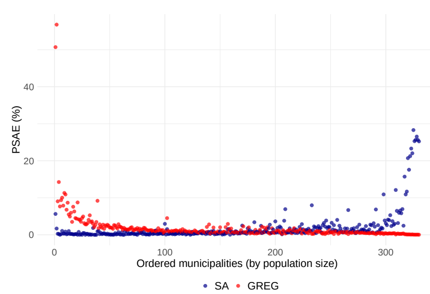

Fig. 1 Comparison of PSAE values between SA and GREG estimates across municipalities, ordered by population size.

Figure 1 shows the PSAE values ordered by municipality size for GREG and SA. It is interesting to note how the two methods complement each other: SA outperforms GREG in the smallest areas, where the integerisation bias (rounding of fractional weights) is most severe; GREG, on the other hand, performs best in medium and large areas, where SA becomes computationally prohibitive. These results suggest a hybrid strategy.

4 Conclusion

Our synthetic populations allow us to evaluate policies and monitor phenomena such as poverty and inequality. This work demonstrates that spatial microsimulation, through reweighting techniques, allows for the reconstruction of local populations even in data-scarce contexts. A hybrid strategy that applies SA to small municipalities (e.g., rural areas) and GREG to larger ones offers an optimal balance between precision and computational feasibility. In our study, for example, we were able to estimate the Gini index in Italian municipalities, analyse its decomposition among labour categories, and use the synthetic population to study regional policies. This work demonstrated how the quality of the synthetic population is strictly conditional on the choice of benchmarks and on a rich survey data to mitigate the zero-cell problem [6]. Researchers should retain flexibility to define benchmarks ex ante based on the specific indicators they intend to evaluate.

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