Modeling Internal Migration in Italy: Strategies to Reduce Campania's Outmigration

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Abstract. **Italy's internal migration has long been characterized by significant flows from the southern regions to the industrialized north. To model and predict these patterns, we extend the parameter-free radiation model with region-specific mobility coefficients α_i, capturing each region's population propensity to leave their place. Calibrated against ISTAT data via nonlinear least squares, our framework reproduces observed migration flows for both a simplified three-region case and the full twenty-region network. Building on this calibrated model, we propose two practical control strategies: an *optimal coefficients* policy that adjusts Campania's mobility coefficient to reduce its net outflow, and a *pinning control* that emulates targeted influxes of international migrants. Both approaches achieve a 50% reduction in Campania's net loss while offering distinct real-world interpretations—economic incentives versus managed immigration—highlighting their complementary roles in restoring Italy's regional demographic balance.**

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1 Introduction

Since the post–World War II economic boom, Italy has experienced significant internal migration from the Mezzogiorno to its industrialized north. Between 1958 and 1963, over 1.3 million southerners, predominantly unskilled laborers, relocated to cities such as Turin and Milan to staff burgeoning factories [contributors, 2024]. After a slowdown in the 1970s, a resurgence began in the 1990s, characterized by young, university-educated adults pursuing careers in the North's expanding service and knowledge sectors [Basile et al., 2019].

Campania remains the largest sender among the southern regions, accounting for nearly 29% of all south-to-north moves in 2022–2023 [ISTAT, 2024a]. ISTAT data indicate approximately 253,000 annual transfers from southern to central and northern Italy, with about 75,000 originating from Campania, resulting in a net loss of about 4.0‰ of the region's population each year [ISTAT, 2024a]. The main destinations are Lombardia (especially Milan) and Emilia-Romagna (notably Bologna), and the majority of migrants are between 20 and 40 years of age with higher education, intensifying a 'brain drain' that accelerates Campania's demographic aging and widens its economic disparities [Basile et al., 2019].

This work aims to model and control the dynamics of Campania's outmigration. In Chapter 2, we introduce a mathematical framework for capturing the demographic dynamics of regional migration. Chapter 3 presents an open-loop analysis of this model, beginning with a three-region case and then extending to all twenty Italian regions. Finally, Chapter 4 proposes and compares two control strategies designed to mitigate Campania's outmigration.

2 Data and methods

In Section 2.1, we present the dynamic migration model—previously applied to human displacement under environmental change in Bangladesh [De Lellis et al., 2021], that governs population flows between regions. Section 2.2 then details the construction of the network of Italian regions. Finally, Section 2.3 describes the model calibration with respect to observed migration data in Italy.

2.1 Formulation of the Migration Model

The Italian peninsula is divided into 20 regions, which serve as the nodes of our migration network. At each node i, the population at discrete time k is denoted $n_i(k)$. Assuming that birth and death rates balance and that there is no net demographic exchange with areas outside the peninsula, the continuity equation [De Lellis et al., 2021] is:

$$n_i(k+1) - n_i(k) = \sum_{j=1}^{N} J(j \to i,\ k) - \sum_{j=1}^{N} J(i \to j,\ k)\,, \tag{2.1}$$

where $J(i \to j,\ k)$ is the migration flux from region i to region j during $[k, k+1)$.

To close the system and capture the effect of economic drivers (e.g. job opportunities), we relate fluxes to the regional populations and a set of mobility parameters α_i. The constitutive relations of the generic flux is:

$$J(i \to j,\ k) = n_i^m(k)\, r_{ij}\big(\mathbf{n}(k)\big) \tag{2.2}$$

where $n_i^m(k) \leq n_i(k)$ is the mobile population, i.e. the number of people living in a region i at time k that could migrate in the time interval $[k, k+1)$; while $n(k)$ is a vector collecting all the region's population at time k; and $r_{ij}(n(k)) \in [0, 1]$ is the migration rate, i.e. the fraction of mobile people of origin i which chooses j as the destination.

The mobile population of each region is linked to the initial population through N parameters $\alpha_i, \cdots, \alpha_N \in (0, 1)$, in the following way:

$$n_i^m(k) = n_(k) - \alpha_i n_i(0). \tag{2.3}$$

The parameters $\alpha_i \in (0, 1)$ modulate each region's migration propensity. Economically, α_i captures how strongly local conditions, such as job availability or quality of life, deter or encourage emigration. Regions with limited opportunities have lower α_i, yielding a larger mobile fraction and hence greater outflows, whereas more attractive regions have higher α_i, reflecting a smaller pool of potential migrants.

The migration rate corresponds to the probability of migration given by the parameter-free radiation model [Simini et al., 2012], which relates the migration tendency from an origin i to a destination j to the populations of both these regions as well as the population of any neighboring region. Specifically it is:

$$r_{ij}\big(\mathbf{n}(k)\big) = \begin{cases} \dfrac{n_i(k)\, n_j(k)}{\big(n_i(k) + n_j(k) + \sum_{l\in\mathcal{N}_{ij}} n_l(k)\big)\big(n_i(k) + \sum_{l\in\mathcal{N}_{ij}} n_l(k)\big)}, & i \neq j, \\ \dfrac{n_i(k)}{\sum_{l=1}^{N} n_l(k)}, & i = j, \end{cases} \tag{2.4}$$

where $\mathcal{N}_{ij} = \{\, l \neq i : d_{il} < d_{ij} \,\}$ is the set of regions closer to i than j, and d_{ij} denotes the distance between region capitals (or centroids). Notice that this formulation captures the deterrent effect of distance and competing opportunities without fitted parameters; indeed, this model reflects the fact that an individual will select its migration destination on the basis of better life opportunities, while seeking to remain close to the origin. Therefore, the summation at the denominator in Eq. (2.4) accounts for intervening opportunities since an individual seeking to migrate or commute from region i to region j will first encounter all of the potential "opportunities" located in regions that lie closer to i than j itself.

2.2 Network description

The geographical area of Italy is partitioned into its regions. In Fig. 1 we report the simpler graph with only three nodes represented by the Sicily, Campania, and Lombardia. A directed network is useful since the migration fluxes may not be symmetric, e.g., more people might move from Campania to Lombardy than vice versa, then the edges direction becomes important. The

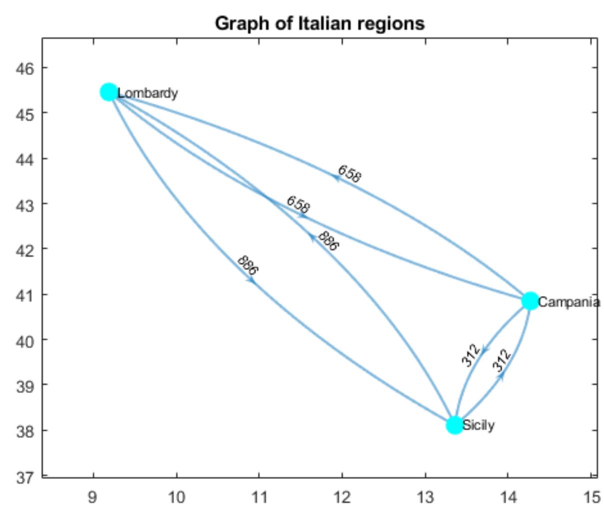

Figure 1: This directed graph has as nodes the Italian regions and as weights on the arcs the distance in kilometers for each regions capital.

distance between each region has been calculated with respect to their capitals and stored in the matrix D that is useful to calculate the migration rate in Eq.2.4 for each couple of origin and destination.

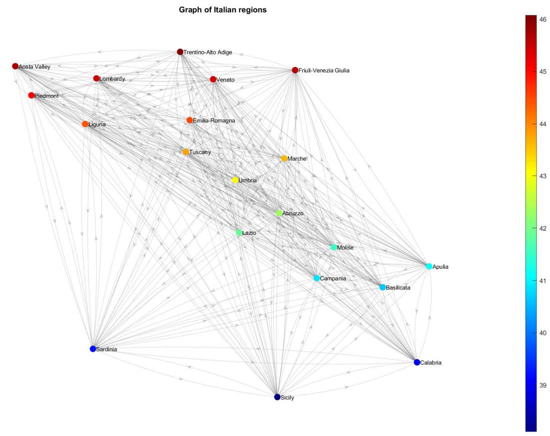

Figure 2: Directed graph of all the twenty Italian regions.

The network topology chosen is an all-to-all graph, since all the regions are connected to each other.

2.3 Calibration of the Migration Model on the ISTAT out-migration statistics

The calibration of the migration model aims to find the set of values $\alpha_1, \ldots, \alpha_N$, where each α_i represents the fraction of inhabitants from region i who attempt to migrate. We expect lower values of α_i in southern regions, where more people tend to migrate compared to northern regions due to less favorable economic conditions.

To capture Italy's asymmetric migration dynamics, different values of α_i are required across regions. The proposed calibration procedure involves solving a non-linear least squares problem to find the set $[\alpha_1, \ldots, \alpha_N]$ that minimizes the sum of squared differences between the observed net internal migration balance s_i, provided by [ISTAT, 2024b], and the model-predicted values $\hat{s}_i$:

$$\min_{\alpha} \sum_{i=1}^{N} (s_i - \hat{s}_i)^2 \tag{2.5}$$

where:

$$\begin{aligned} \hat{s}_i &= \frac{\sum_{k=1}^{N_t} \left(J^i_{\text{in}}(k) - J^i_{\text{out}}(k)\right)}{\frac{\bar{n}_i + n_i(0)}{2}} \\ J^i_{\text{in}}(k) &= \sum_{j=1}^{N} J(j \to i, k) \\ J^i_{\text{out}}(k) &= \sum_{j=1}^{N} J(i \to j, k) \end{aligned} \tag{2.6}$$

Note that the time scale of the migration process is not important, as the net internal migration balance converges to zero at steady state. Therefore, calibrating the model using net migration data is appropriate, assuming the model predictions align with the time scale over which the data were collected.

The results of the calibration procedure are shown in the Chapter 3 for both three or all the twenty regions.

3 Open-loop Analysis

In this chapter, we perform an open-loop analysis of the nonlinear model in Eq. (2.1), calibrate it against observed migration data, and present prediction results for both the three-region case (Section 3.1) and the full 20-region network (Section 3.2).

3.1 Case Study: Three Regions — Sicily, Campania, and Lombardy

In this section, the migration of the population in case of only three regions: Sicily, Campania and Lombardy is analyzed.

The calibration of the model for the three coefficients $\alpha_1, \alpha_2, \alpha_3$ makes the prediction of the internal migration balances ($\hat{s}_i$) slightly different from the observed ones (s_i) as shown in the Table 1, however, the migration trend from the south to the north is captured as showed in Fig.3.

The biggest difference in the predicted net flux relies in the number of population gained for the Lombardy that is more than two times the observed value. The coefficients found are:

$$\alpha = [0.3734\ 0.3059\ 0.6674]$$

.

The region with the highest population (Lombardy) has the biggest initial probability of having out-migration because the radiation model predicts more opportunities in more populated regions; this is reflected by higher values of $r_{ii}(0)$ as shown in Table 1.

Region	s_i	$\hat{s}_i$	Net flux observed	Net flux predicted	$r_{ii}(0)$
Sicily	-2.8	-2.2	-13367	-10622	0.23
Campania	-3.3	-2.6	-18373	-14639	0.27
Lombardy	1.3	2.5	+13063	+25261	0.49

Table 1: In the table there are: the values of observed s_i and predicted $\hat{s}_i$ net migration balance and their relative net flux, the probability of not migrating for the population of region i at the initial time $r_{ii}(0)$.

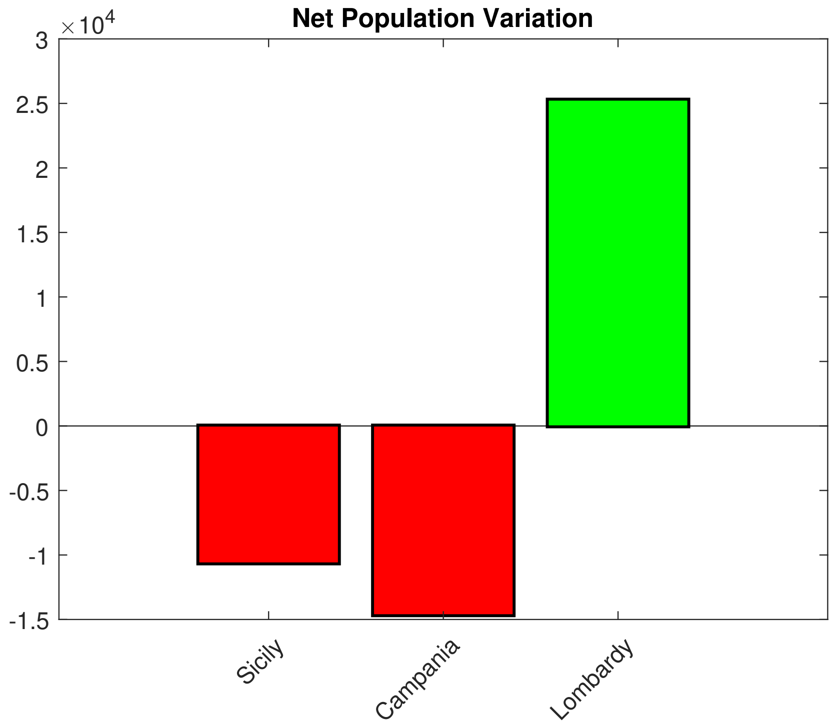

Figure 3: The net population variation for each region is calculated as the difference between the steady state population and that at the first time step $\bar{n} - n(0)$. A positive gain in the population is showed in green and a negative in red.

The migration is a transient phenomenon in which the negative migration flows of the south cause positive flows for the north. However, in steady state, the fluxes compensate each other to respect the continuity equation 2.1 then, the net migration flux goes to zero as in Fig.4. The population number also reaches a steady state value. The Lombardy grows of 0.25‰ its population, while the southern regions register a loss of at least 0.20‰ with respect to the initial population value (Fig.5).

Notice that the values of J represents the migration fluxes occurring in each time step for each couple of origin and destinations. The steady state values $\bar{J}$, represents the fluxes we must have to reach a steady state.

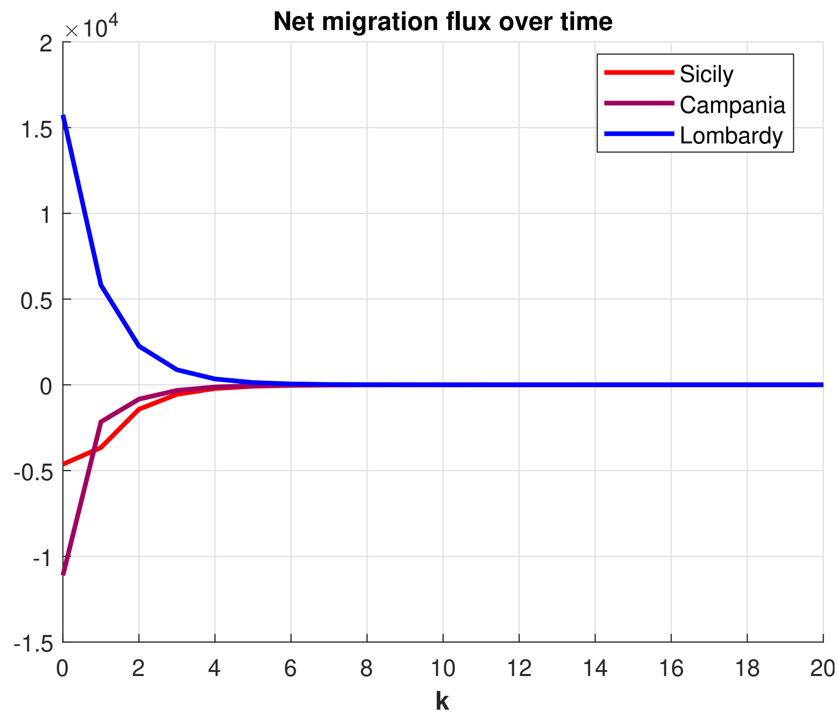

Figure 4: The figure shows the net migration flux of each region for every time step k, it is calculated as $\sum_{j=1}^{N} J(j \rightarrow i, k) - J(i \rightarrow j, k)$.

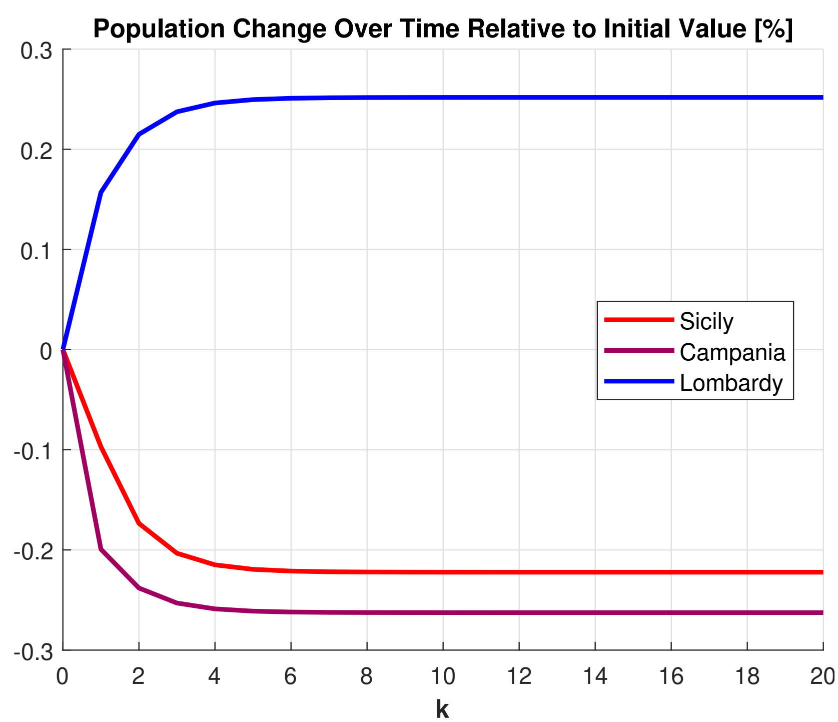

Figure 5: The change over time of the population is calculated as $\frac{n(k)-n_0}{n(0)} \cdot 100$
.

3.2 Case Study: All Twenty Italian Regions

Identification of the coefficients $\alpha_i, \cdots, \alpha_N$ in the case of twenty regions ($N = 20$) gives predictions of the internal migration balance in good agreement with the observed data from [ISTAT, 2025] as shown in Fig. 7 and quantitatively in Table 2. In particular, the net predicted flux of Lombardy is more accurate than in the case with only three regions (see Tab. 1).

The fitted coefficients α_i show two clear patterns:

- **Bigger regions "keep" more people.** Whenever $n_i(0)$ is larger, α_i goes up, meaning a smaller share of the population is considered "mobile." This matches the idea that big cities and dense areas offer more jobs, services, transport links and social networks—so fewer people feel the need (or have the chance) to leave.
- **Extra friction in certain small regions.** Some places (e.g. Sicily) get a surprisingly high α_i despite their smaller size. That's because the basic radiation model would otherwise over-predict how many people leave. To correct this, α_i absorbs local hurdles like ferry costs and travel times, housing shortages, strong family or community ties, or even under-reported moves.

Overall, α_i acts as a simple, region-by-region "friction" factor that improves the pure radiation predictions—built only on populations and distances—to fit the real migration data.

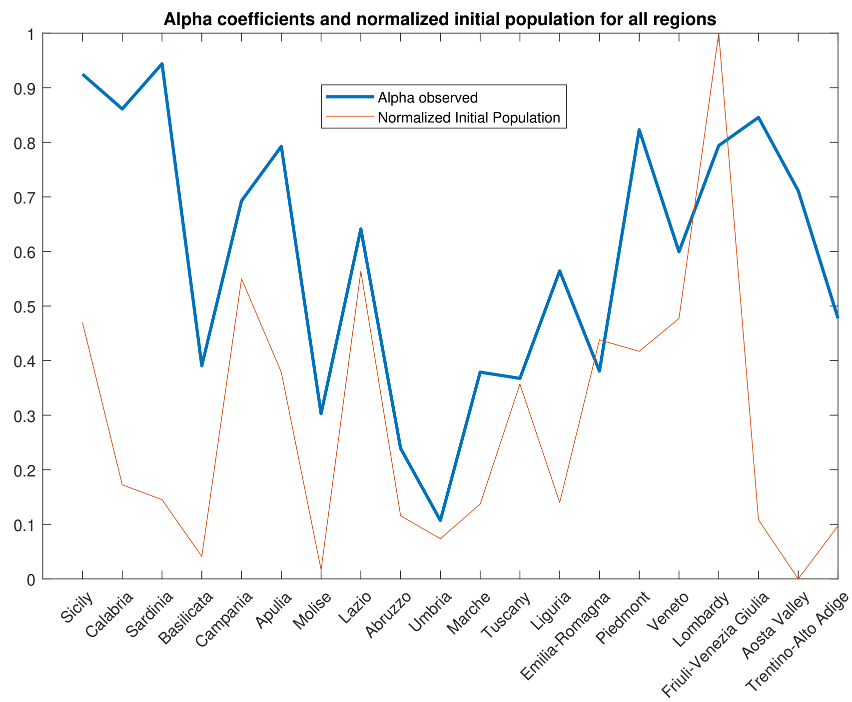

Figure 6: The figure shows the comparison between the alpha coefficients obtained from the calibration procedure considering all the twenty italian regions and their relative normalized value of the initial population, i.e. $n_{norm} = \frac{n(0) - min(n(0))}{max(n(0)) - min(n(0))}$.

Region	s_i	$\hat{s}_i$	Net flux observed	Net flux predicted	$r_{ii}(0)$
Sicily	−2.8	−2.4	−13367	−11469	0.08
Campania	−3.3	−3.4	−18373	−19031	0.09
Lombardy	1.3	1.48	+13063	+14903	0.17

Table 2: Considering the case of all the regions, this table shows some values for the three regions of reference. The values are: the observed s_i and predicted $\hat{s}_i$ net migration balance and their relative net flux, the probability of not migrating for the population of region i at the initial time $r_{ii}(0)$.

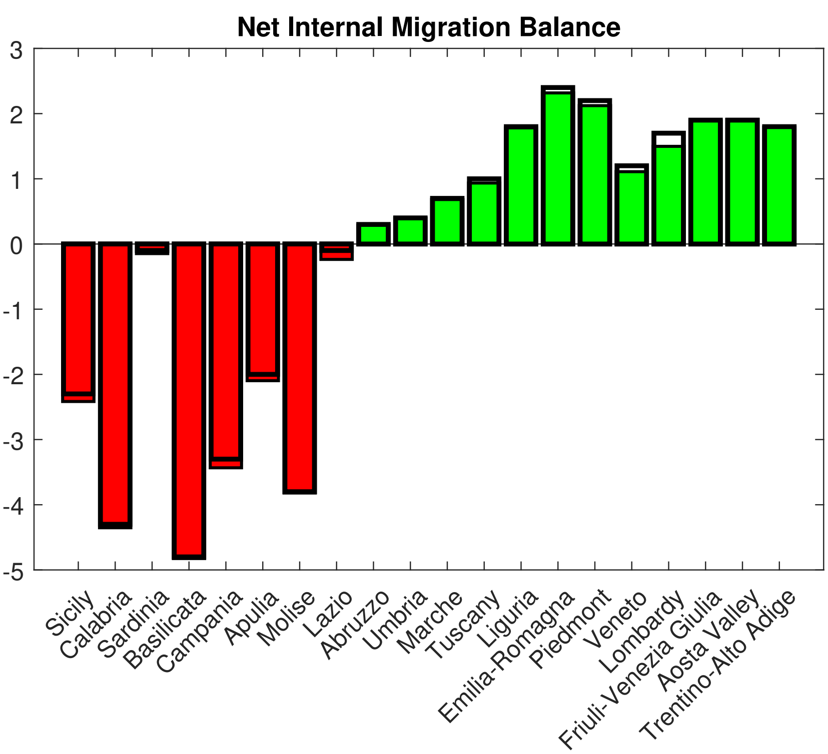

Figure 7: The figure shows the comparison between the predicted net migration balance (full colored bars) and the observed ones (dark segments) from [ISTAT, 2025].

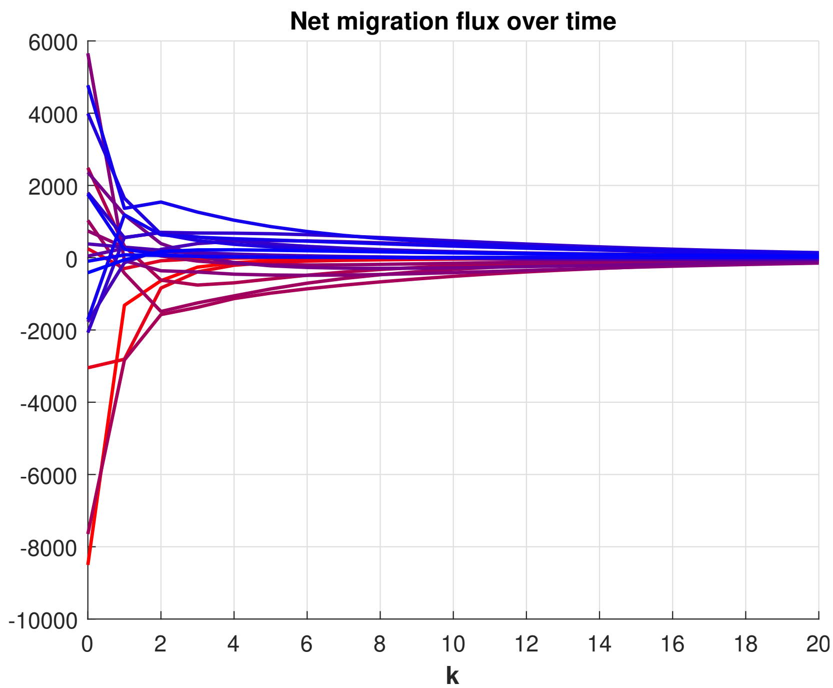

Figure 8: The figure shows the evolution of then net migration flux over time with a base color of red for the southern regions blending to blue for the northern regions.

4 Control Strategy to mitigate Campania's out-migration

In this chapter, we develop two control strategies to reduce out-migration from Campania.

First, Section 4.1 introduces an *optimal coefficients* policy: we prescribe a target internal migration balance for Campania and then compute the adjustments to its α_i values that are required to steer the mobile population toward that goal.

Second, in Section 4.2 we formulate a *pinning control* approach. Here, we translate the desired net migration balance into a target post-transient population n_i^* and add a feedback term to the continuity equation:

$$n_i(k+1) - n_i(k) = \sum_{j=1}^{N} J(j \to i,\ k) - \sum_{j=1}^{N} J(i \to j,\ k) - \delta_i\, K_i\big(n_i(k) - n_i^*\big)\,, \tag{4.1}$$

where $\delta_i = 1$ only for the pinned (southern) regions and K_i sets the feedback gain. The term $-K_i(n_i - n_i^*)$ represents the number of individuals to inject (or remove, i.e., immigration of people from abroad) each time step in order to achieve the chosen migration balance.

In the end, we apply the control strategies developed considering all twenty Italian regions, the results are shown in Section 4.3.

4.1 Optimal coefficients policy for three regions

In the case of three regions, it is possible to increase by nearly 50% the net migration balance s_i for the Campania region, with respect to the observed value $s_i = -3.3$, by imposing $s_i = -1.5$. This can be achieved by finding optimal values of $\alpha^* = [0.3732\ 0.3065\ 0.6669]$, we can notice that the coefficient for Campania is slightly decreased with respect to that found in Sec.2.3 and the net population variation for Campania reduced by half as shown in Fig.9.

In reality, a decrease in the population willing to leave a region can be achieved by e.g., more job opportunities and economic incentives.

Note that in the optimization we allow all coefficients α_i to vary simultaneously. However, the qualitative impact on the net change in population is virtually identical if we vary only the coefficient of Campania. In both cases we see a general reduction in inter-regional mobility: Lombardy receives fewer migrants overall, and regions like Sicily must supply more to maintain the same target population (and thus income level) in the north. This makes sense: If Campania retains a larger share of its population, the positive migration needed by Lombardy must be compensated by increased outflow from other regions, Sicily being the next largest contributor.

This method causes a general reduction in population mobility; in fact, the number of inhabitants of Campania that leave the region decreases over time, as shown in Fig.10. This means that the population of Campania is more likely to the its initial value.

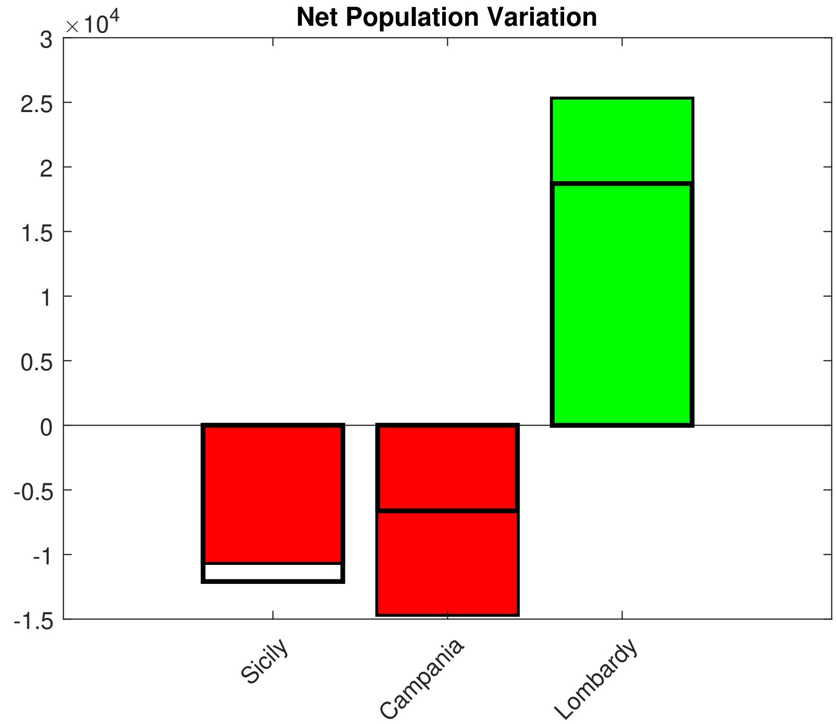

Figure 9: The figure shows the effect of the optimal α_i values found to half increase the net population migration of Campania (unfilled segments).

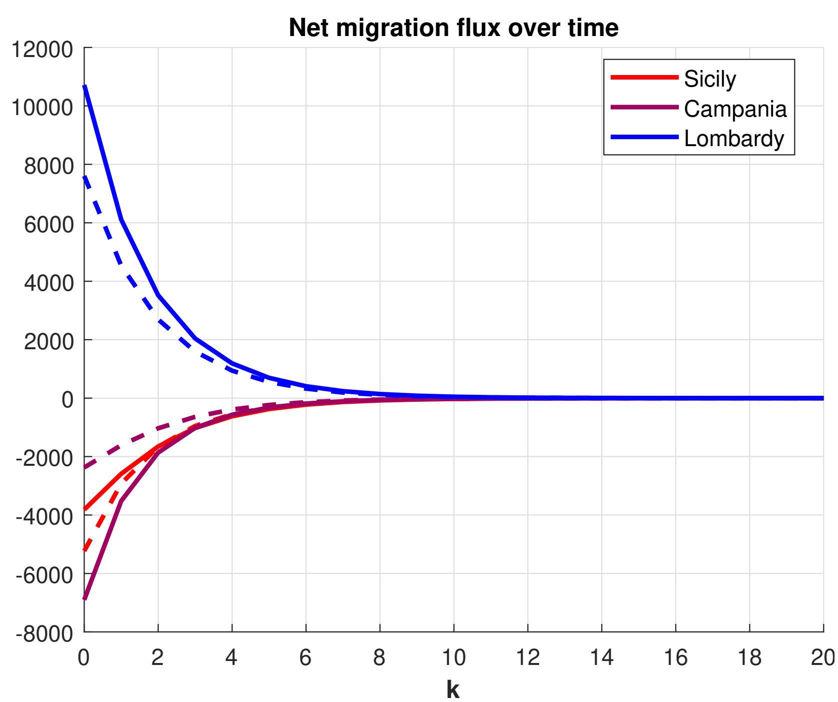

Figure 10: In the figure the net migration flux over time of each region is compared for each time step. The results with the optimal coefficients (dashed lines) give a less negative migration flux for Campania with respect to the open-loop case (solid lines).

4.2 Pinning control for three regions

A pinning control has been implemented to reduce by 50% the out migration of Campania region. We compare the results with respect to the predicted Italian migration scenario described in Tab.1. The control goal is achieved as shown in Fig.11 where the population decrease in Campania is reduced by half by using $K_i = 0.5$ and $n_i^* = 5568025$, this latter has been chosen to have a net decrease in the population of only 7000 people with respect to the initial value.

The control input here can be viewed as an "injection" of people into Campania—analogous to an influx of international migrants—which drives larger population changes across the entire network. In Figure 13, you can see that this pinning input starts out strongly positive, reflecting the initial arrival of newcomers. Over time it decays, crosses zero, and settles at a small negative value. That negative steady state arises because, even after the initial influx, the control objective for Campania still requires net emigration to balance the system. In other words, the input's time profile captures both the surge of migrants coming in and the subsequent outflow needed to reach the desired equilibrium.

However, the presence of an international migration toward a region has the advantage of reducing the overall south out-migration fluxes, as it is for Sicily. It will more clear considering all the twenty italian region in the Section 4.3.

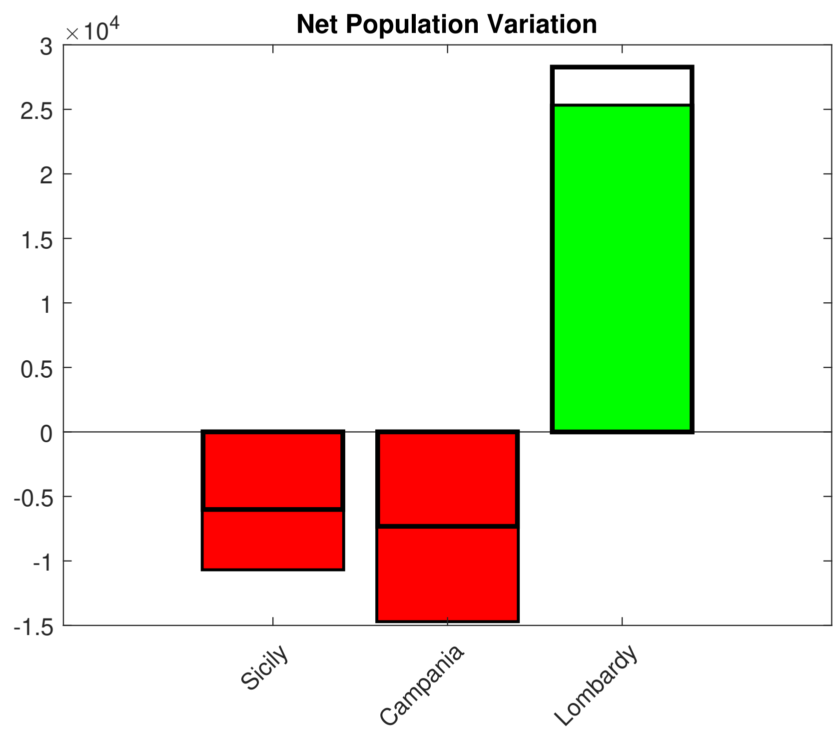

Figure 11: In this figure we compare the net population variation ($\bar{n} - n_0$) obtained by using a pinning control input for the Campania region (unfilled segments) with respect to the initial predicted scenario without any control.

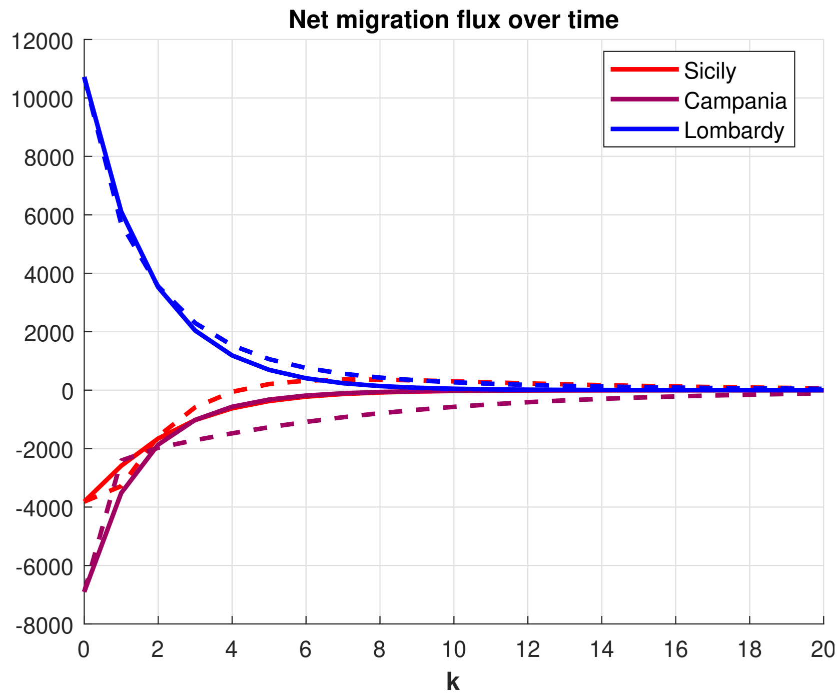

Figure 12: The figure shows the

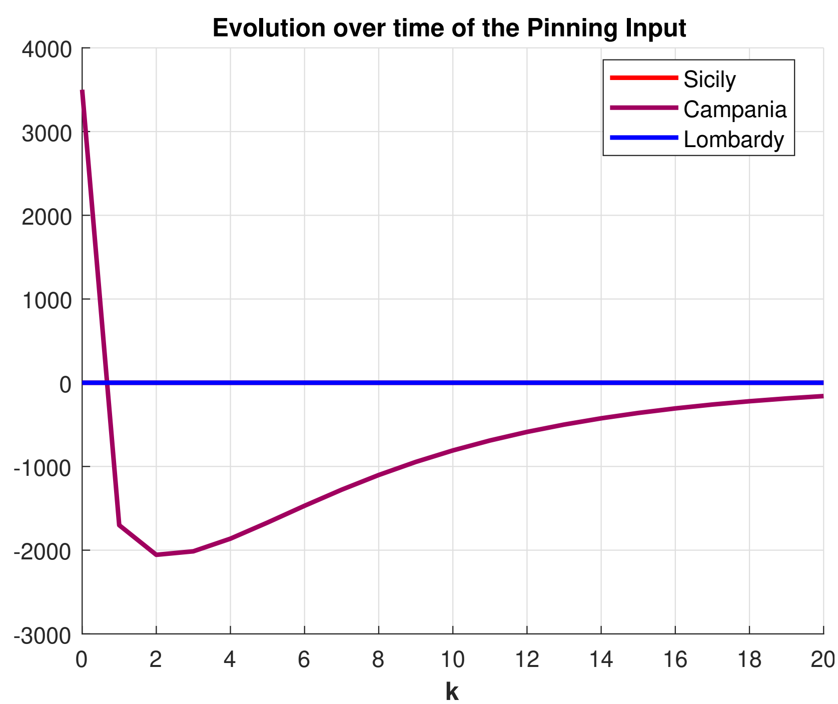

Figure 13: The figure shows the pinning control input in the case of three regions and only the Campania node is pinned.

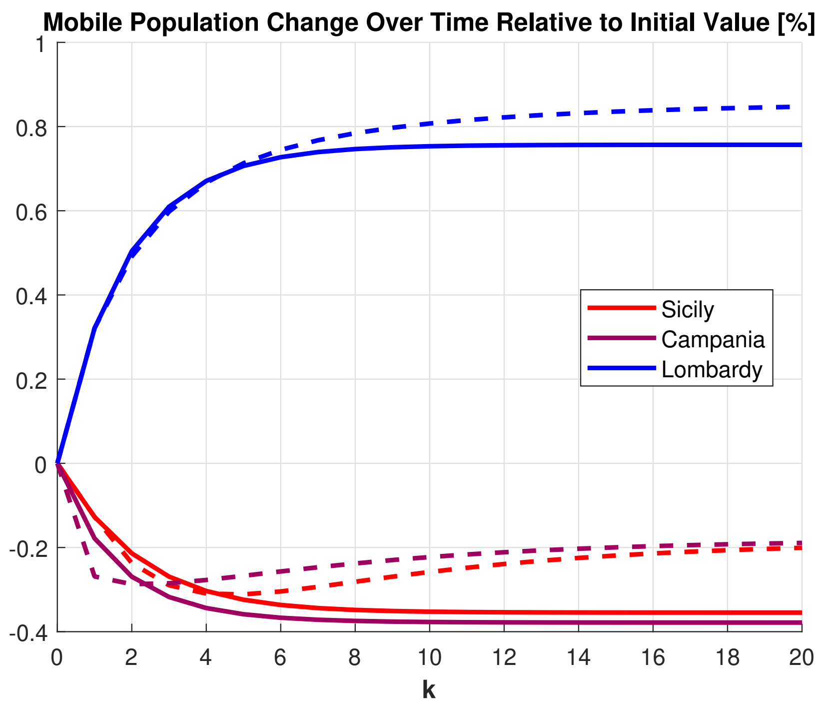

Figure 14: The mobile population in presence of pinning control for Campania is represented by dashed lines and it is compared with the reference scenario (solid lines). The values we represent is the normalized mobile population, i.e. $\frac{n_m(k)-n_m(0)}{n_m(0)} \cdot 100$.

4.3 Migration control for all twenty Italian regions

In this paragraph we aim to control the migration from Campania considering all twenty Italian regions.

The goal of reducing the migration from Campania by nearly 50% can be reached by calculating the optimal coefficients α. With limited effects on the other population as shown in Fig.15. As expected, this approach reduces the Campania mobile population and, as a consequence, the positive migration of the northern regions.

By pinning only Campania with a gain of $K = 0.5$, we achieve the control target by boosting its net migration up to $-11\,938$. However, this upward "injection" of people into Campania raises the overall mobile population, so neighboring regions—especially those in the central also absorb more migrants (see Fig. 16). The same effect appears when we pin additional nodes: every new injection region adds more mobile individuals into the system, which in turn drives Italy's total net migration even higher.

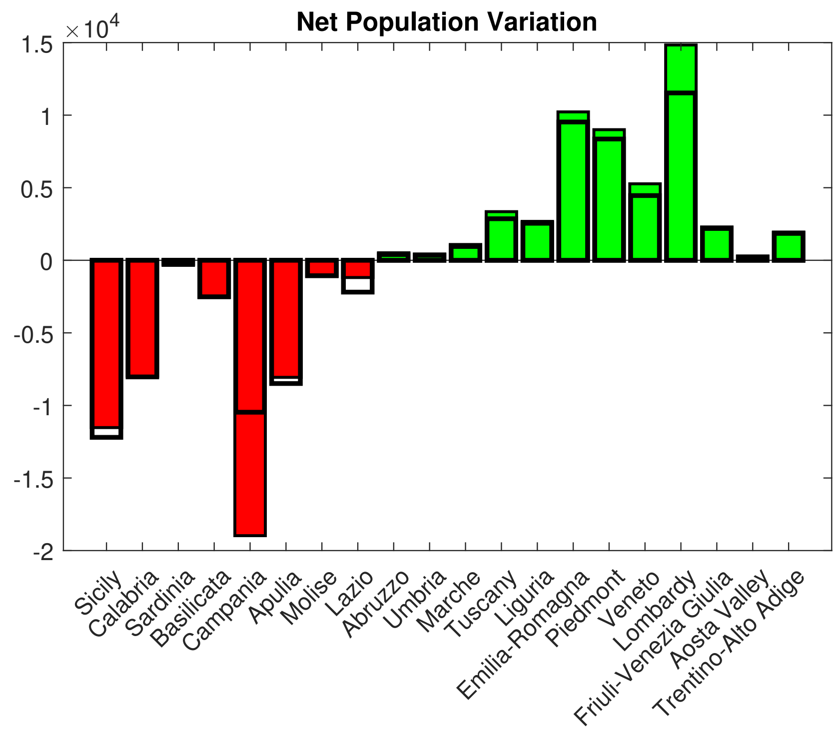

Figure 15: The figure shows the net population variation comparing the results obtained calculating the optimal α for the Campania region (dark segments) with that of the open-loop analysis (fully colored bars). In the case of twenty regions.

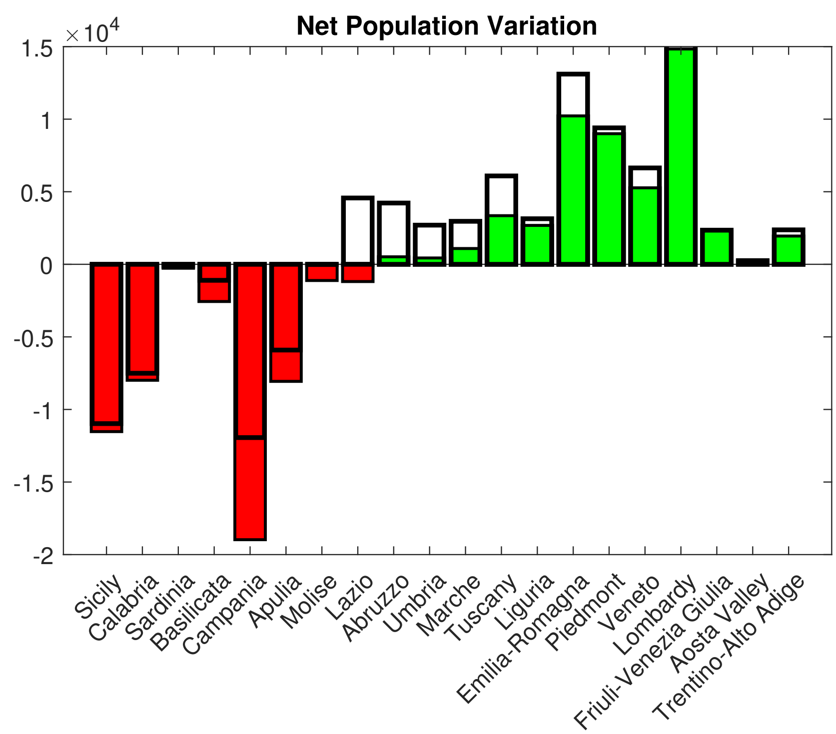

Figure 16: Pinning control of twenty regions

5 Conclusions

In this work, we have developed and validated a nonlinear migration model for Italy's twenty regions by combining the parameter-free radiation model with region-specific mobility coefficients α_i into a fully nonlinear predictive model for each region (i.e. nodes of the network). Calibration against ISTAT data via nonlinear least squares demonstrated that our framework accurately reproduces both the magnitude and the spatial pattern of historical south-to-north flows considered.

To mitigate Campania's persistent outmigration, we proposed two control schemes. First, an *optimal coefficients* policy adjusts Campania's own α so that its net migration balance improves by 50 ‰—a change that could be realized in practice through targeted economic incentives and job-creation programs which reduce the number of people willing to leave the region. Second, a *pinning control* injects an external "influx" of migrants into Campania, emulating increased international immigration. Both approaches succeed in reducing Campania's net loss, but they exhibit distinct transient behaviors: the α-optimization slows internal outflow directly, whereas pinning maintains the original emigration rate while compensating it with a timed influx.

Finally, when extended to all twenty regions, each method preserves its properties: reducing Campania's mobile fraction also reduce the positive inflows into northern regions, and conversely, injecting newcomers in Campania slightly boosts regional mobility elsewhere. These trade-offs underscore the importance of system-wide planning—whether by improving local conditions or by managing international arrivals—to achieve sustainable demographic balance across Italy.

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