

Università degli Studi del Molise
Dipartimento di Economia



ECONOMICS AND STATISTICS DISCUSSION PAPER
No. 103/26

Far, far away municipalities: Has the Italian National Strategy for Inner Areas helped in reducing distances from essential services?

**Angela Stefania Bergantino
Nicola Caravaggio
Mario Intini
Giuliano Resce**

The Economics and Statistics Discussion Papers are preliminary materials circulated to stimulate discussion and critical comment. The views expressed in the papers are solely the responsibility of the authors.

(This page intentionally left blank.)

Far, far away municipalities: Has the Italian National Strategy for Inner Areas helped in reducing distances from essential services?

 Angela Stefania Bergantino^a,  Nicola Caravaggio^{b,†,*},  Mario Intini^a, and  Giuliano Resce^b

^a*Department of Economics, Management and Business Law, University of Bari “Aldo Moro”, Bari – Italy; Laboratory of Applied Economics, University of Bari “Aldo Moro”, Bari –Italy*

^b*Department of Economics, University of Molise, Campobasso – Italy*

[†]nicola.caravaggio@unimol.it

Abstract

This study evaluates whether the Italian National Strategy for Inner Areas (SNAI) has improved accessibility to essential services in peripheral municipalities. Introduced in 2014, the SNAI targets territories characterized by demographic decline and limited access to key services such as schools, healthcare, and transport infrastructure. Using real-time travel data from OpenStreetMap (OSM) and Tom Tom, we develop a replicable framework to monitor driving times to service hubs for more than 7,600 Italian municipalities. Our tool replicates the methodology used to identify Inner Areas during the second programming cycle of the SNAI (2021–2027). Applying this framework, we update the classification of Inner Areas for 2025 and document a 20% increase in their number compared with the latest official classification. We then estimate a two-period Difference-in-Differences (DiD) model combined with Propensity Score Matching (PSM) to compare municipalities targeted by the strategy with similar non-targeted areas. The results suggest that municipalities included in the SNAI did not experience improvements in accessibility during the period considered. On average, treated municipalities display a modest increase in travel times of about 2.4 minutes relative to comparable Inner Areas not included in the strategy. These findings indicate that, while the SNAI may contribute to broader territorial development objectives, measurable improvements in road accessibility remain limited.

Keywords: place-based policy, inner areas, policy evaluation, Italy.

JEL Classification: C31, O18, R58.

1 Introduction

In recent decades, regional inequality has re-emerged as an urgent consideration in economic research, propelled by the disparate consequences of globalization, fiscal austerity, and demographic shifts across European regions. Italy, characterized by complex geography and pronounced historical socio-economic heterogeneity, provides a salient context for examining spatial disparities and assessing the effectiveness of territorial cohesion policies. At the forefront of Italy's response is the National Strategy for Inner Areas (*Strategia Nazionale Aree Interne* – SNAI) which was developed in 2014 through the Partnership Agreement with the European Commission (EC) that would regulate regional policy until 2020.

The origin of SNAI can be traced to the document published by [Barca](#) in 2009 that proposed a revised approach to European cohesion policies with a different bottom-up strategy rooted in the concept of a place-based development approach ([Barca et al., 2012](#); [Barca, 2019](#)). The same Lisbon Treaty of 2009 stressed how an objective of the European Union (EU) is the necessity to recognize the highly diversified characteristics of territories. It is not a case that this approach that reshaped the European regional politics came from the Italian background whose history of economic thought is rich in long-standing contributions to territorial differences ([Rossi-Doria, 1958](#)).

The SNAI, developed by a dedicated technical committee, covered the programming period 2014–2020. The strategy targets marginal territories characterized by depopulation, population ageing, and limited access to essential services. In particular, distance from services played a crucial role in identifying these areas. The classification relied on accessibility to key public services such as secondary schools, railway stations, and hospitals. Using this criterion, the strategy identified more than 1,000 municipalities as ‘Inner Areas’, corresponding to approximately 17% of the Italian territory. These municipalities became eligible to receive targeted resources under the strategy. The primary objective of the SNAI is to reverse the gradual decline of these territories and counteract the negative demographic dynamics that characterize them ([Lucatelli, 2022](#)).

With the subsequent programming period 2021–2027, the classification of Inner Areas was revised and the number of beneficiary municipalities expanded to more than 1,900. Nevertheless, the broader set of marginal territories—defined as municipalities whose driving time to the nearest service hub exceeds 27.7 minutes—is considerably larger, covering almost 60% of the Italian territory.

Overall, the strategy has mobilized approximately € 1.76 billion in resources, of which roughly € 300 million were allocated during the first programming cycle. These funds also include resources from the Italian National Recovery and Resilience Plan (NRRP). Funding is disbursed following the approval of specific framework agreements developed by local institutions, approved by the relevant regional authorities, and coordinated by national technical committees. Interventions cover a wide range of areas, including support for local entrepreneurship, energy investments, cultural heritage initiatives, and infrastructure improvements. In the second programming cycle, part of the resources has been explicitly earmarked for improving road infrastructure.

Despite a decade of implementation, the effectiveness of the SNAI in reducing territorial disparities remains debated. While policy attention has increased and a growing empirical literature has examined Inner Areas (*e.g.*, Gallo and Pagliacci, 2020; Benassi *et al.*, 2024; Compagnucci and Morettini, 2024; Di Matteo, 2025; Monturano *et al.*, 2025; Bolzoni *et al.*, 2026), rigorous evaluations of the strategy remain relatively limited. In particular, little evidence exists regarding one of the most fundamental dimensions of territorial exclusion: physical access to essential public services.

This article seeks to contribute to this debate by evaluating whether municipalities included in the 2021–2027 SNAI programming period experienced reductions in travel times to service hubs relative to untreated municipalities. To do so, we first develop a replicable framework for monitoring accessibility conditions in real time by combining data from OpenStreetMap (OSM) and TomTom. This approach allows us to estimate actual driving times under typical weekday conditions and provides a potential monitoring tool for policymakers. Importantly, the methodology replicates as closely as possible the approach adopted in the official SNAI 2021–2027 classification, which also

relied on real-time Tom Tom data.

The updated map of Inner Areas for 2025 based on real-time travel data reveals an expansion of territorial marginality compared with the latest official SNAI classification. Using the same threshold adopted in the SNAI 2021–2027 classification (27.7 minutes), the number of municipalities classified as Inner Areas increases to 4,608, representing an additional 775 municipalities (+20.2%). Overall, Inner Areas now account for 58.4% of Italian municipalities, 67.4% of the national territory, and 28.2% of the population. The increase is particularly pronounced in Northern regions, which were previously characterized by a smaller number of Inner Areas. Against this background of increasing distances from essential services, the key question is whether municipalities targeted by the SNAI experienced improvements in accessibility relative to comparable municipalities.

For the empirical analysis we employ a two-period Difference-in-Differences (DiD) model combined with a Propensity Score Matching (PSM) procedure in order to improve comparability between treated and control municipalities. The analysis focuses on two periods: 2019, when Inner Areas were reclassified for the SNAI 2021–2027 programming cycle, and 2025, for which we recalculated travel times to essential services using updated routing data.

The empirical evidence suggests that municipalities targeted by the SNAI did not experience improvements in accessibility during the period considered. On average, treated municipalities display a modest increase in travel time to service hubs—approximately 2.4 minutes relative to comparable Inner Areas not included in the strategy. Although the magnitude of this effect is relatively small in absolute terms, it indicates that accessibility conditions in already remote territories have not improved over time. When the sample is divided across macro-regions, the estimated coefficients remain statistically insignificant, suggesting that the relationship between SNAI participation and changes in accessibility does not differ systematically between Northern–Central and Southern regions.

Taken together, these results suggest that while the SNAI may contribute to other policy objectives—such as strengthening local services, tourism promotion,

or social cohesion—it has not yet produced measurable improvements in road accessibility. One possible explanation is that SNAI resources, particularly in the earlier phases of the strategy, were not strongly conditional on investments in transport infrastructure and may have been directed toward other local development priorities.

The remainder of the article is structured as follows. Section 2 reviews the literature on studies concerning the Italian SNAI. Section 3 outlines the research design, including data, sample, and methodology. Section 4 presents and discusses the results. Finally, Section 5 concludes the manuscript.

2 Literature review

The economic literature focusing on the study of the role and impact of place-based policies has developed particularly over recent years (*e.g.*, [Busso *et al.*, 2013](#); [Neumark and Simpson, 2015](#); [Partridge *et al.*, 2018](#); [Duranton and Venables, 2018](#)). The Italian case, with its SNAI, emphatically represents a preeminent case study with a scientific landscape rooted within the historical North-South divide literature and development interventions aimed at filling this gap since the 1950s. The works are characterized by a multidimensional approach that spans regulatory, socio-economic, environmental, and organizational aspects. The works of [Cotella and Brovarone \(2020\)](#) and [Rossitti *et al.* \(2021\)](#) provide the framework within which selection criteria, cohesion objectives, and governance tools are defined, while [Moscarelli and Fera \(2024\)](#) propose a comparison between the two strategies. The present literature review focuses primarily on economic-oriented academic contributions.

The concept of Inner Areas can also be associated with and placed within the literature of ‘left behind’ places, a term which became popular right after the Great Recession ([Pike *et al.*, 2024](#); [de Vega Perancho *et al.*, 2025](#)). The theoretical contributions of [Rodríguez-Pose \(2018\)](#) relevant to the phenomenon of the “revenge of the places that don’t matter” have underscored the link between territorial decline and populist waves, arguing that the marginalization of places—rather than individual poverty—fuels anti-system sentiment. [Barca](#)

et al. (2012) contrasted place-based and place-neutral approaches, advocating for a balance between efficiency and inclusion. Iammarino *et al.* (2019) documented how the concentration of resources in “superstar cities” exacerbates regional disparities in Europe, while Adamiak *et al.* (2024) analyzed “territorial revenge” phenomena in Poland, reaffirming the need for multilevel and participatory territorial strategies.

The study conducted by Monturano *et al.* (2025) found that, in the first two years following the initial round of funding under the SNAI, there were no statistically significant changes in the migration flows of recipient municipalities. This lack of immediate response suggests that demographic transformations—a major goal of this policy—require a longer time horizon to fully unfold, reflecting adaptation and residential choice processes that do not manifest in the short term.

Alongside these findings, the authors evaluated the role of SNAI in entrepreneurship and the creation of new economic activities. They estimated an average annual increase of 4.23 new productive plants in the treated municipalities, a result that highlights not only the direct effect on target areas but also the ability to generate positive spillovers in neighboring municipalities, confirming the existence of spatial diffusion processes in economic activity. In line with this, Mastronardi and Romagnoli (2020) documented the crucial role of community-based cooperatives (CBCs), created to address collective needs – ranging from elderly care to forest and waterway maintenance – which have triggered regeneration processes of so-called “sleeping resources” and the strengthening of social capital, producing clear benefits for the entire local social and productive fabric, suggesting their greater involvement could strengthen regional policy outcomes. Similarly, ancient transhumance routes (*i.e.*, *tratturi*), especially in regions like Molise, represent valuable yet underutilized cultural and tourism assets. Their preservation and enhancement through targeted policies could further support place-based development strategies (Mastronardi *et al.*, 2021).

Employment is another area in which the use of localized spatial methodologies reveals relevant impact heterogeneities even within small regions. Benassi

[et al. \(2024\)](#) applied a geographically weighted regression (GWR) to Molise municipalities for the period 2011–2019 and showed that the female employment rate influenced demographic dynamics in different ways: in some areas, this variable strongly supported population growth, while in others, the relationship was virtually negligible. This underscores the ineffectiveness of standardized policies and points to the need to tailor support interventions for female labor force participation to local specificities, focusing efforts where demographic returns are highest.

The tourism sector also shows some interesting results as demonstrated by [Di Matteo \(2025\)](#) which analyzed the impact of SNAI funds on tourist presence between 2014 and 2022, recording an average increase of 6% in overnight stays in inner municipalities. However, territorial heterogeneity is quite marked: in Northern Italy, the increase is mainly driven by international tourism, while in the South, domestic visitors largely prevail. These differences underscore the importance of tailoring tourism promotion strategies to specific local vacations and existing infrastructure.

The relationship between resident income and local public spending represents another important area of investigation. [Romagnoli et al. \(2022\)](#) applied a multilevel model to the municipalities of Marche, Abruzzo, and Molise for the period 2008–2016, showing that allocations for environmental protection, tourism, and the enhancement of cultural heritage contributed to an increase in per capita income of approximately 1% for each additional percentage point of spending. Conversely, spending on primary education was associated with a decrease in income, likely due to inefficiencies in resource use in contexts characterized by low levels of specialization.

[Gallo and Pagliacci \(2020\)](#) examined the relationship between Inner Areas and income inequality in Italy during the period 2012–2015. Their findings indicate that the presence of Inner Areas is associated with a reduction in both mean and median gross income, accompanied by an increase in the Gini index, thereby exacerbating territorial income inequality. These effects are particularly pronounced in Central and Southern Italy, where Inner Areas play a more substantial role in driving disparities. The authors argue for the

necessity of targeted interventions, such as those envisaged by the SNAI, to strengthen essential services and mitigate inequality in these vulnerable territories. Nonetheless, [Guzzardi and Morelli \(2024\)](#) have shown that no systematic evidence on top income concentration existed for these areas: municipalities with lower services-accessibility do not necessarily have higher inequality.

The quality of life (QoL) in Inner Areas has been measured by [Bertolini and Pagliacci \(2017\)](#), who developed a non-compensatory composite indicator at provincial level. Spatial analysis revealed a pattern of autocorrelation: clusters of regions with high QoL tend to mutually reinforce each other, while areas marked by high marginalization remain trapped in a downward spiral of decline. This finding highlights the importance of accounting for both positive and negative territorial spillovers in the design and implementation of public policies.

Several authors have reflected on the SNAI’s long-term effectiveness and its structural challenges. Commencing with the work of [Perchinunno *et al.* \(2019\)](#), their findings stress the limitations of the classification adopted by the first SNAI. Later, both [Benassi *et al.* \(2024\)](#) and [Compagnucci and Morettini \(2024\)](#) emphasize the importance of local institutional quality and administrative capacity in shaping the actual implementation of the strategy. They highlight the limitations of the current top-down classification system based on accessibility to essential services, which risks overlooking intra-regional heterogeneity and the real needs of disadvantaged municipalities. Some municipalities identified as Inner Areas show no signs of demographic decline, while other truly fragile areas are excluded from policy benefits. Their findings suggest a need to revise the operational logic of SNAI by incorporating regional-scale demographic monitoring and more flexible, bottom-up approaches for defining intervention areas. A standardized policy framework, they argue, risks misallocating public resources and failing to deliver results in areas most in need.

Beyond the Italian context, international comparisons enrich the discourse on marginal areas. In France, the “France Ruralités” program, launched in 2023, redefines fragile rural zones based on indicators of accessibility, population density, and aging, promoting incentives for service densification and support

for agriculture (ANCT, 2025). The “España vaciada” represents a historical phenomenon of rural exodus, the debate about which has recently been rekindled in Spain (Rodríguez-Rejas and Díez-Gutiérrez, 2021).

In Japan, community-based projects (*machizukuri*) are used in counterpoise with top-down urban planning initiatives (*toshikeikaku*) (Nakajima and Murayama, 2024), both aiming to regenerate small towns. Meanwhile, the counter-urbanization trend—exemplified by the Local Revitalisation Cooperator (LRC) initiative, also known as *chiiki okoshi kyōryokutai*—highlights how the settlement of new urban residents can help revitalize rural communities (Zollet and Qu, 2024). In contrast, in the United States, investment in tribal casinos (Akee *et al.*, 2025) represents a place-based policy case aimed at creating economic opportunities in marginalized territories.

3 Data and methodology

3.1 Institutional framework

The identification of Italy’s so-called Inner Areas has its roots in the country’s long-standing tradition of economic discourse on territorial disparities, dating back to Rossi-Doria (1958). The origins of SNAI can be traced back to Barca’s 2009 report, which proposed a place-based, bottom-up approach to European Cohesion Policy (Barca *et al.*, 2012; Barca, 2019).

These areas are marked by high levels of marginalization resulting from sustained emigration, social and productive decline, land abandonment, and significant landscape transformations. This condition stems from a long history of out-migration that began during Italy’s urbanization process in the 1950s—a gradual dynamic that has left these territories vulnerable to economic downturns and natural hazards (Modica *et al.*, 2021).

The development of the Italian SNAI began in 2011 and, shortly afterwards, a specific technical research group was created between 2013 and 2014 by the Italian Agency for Territorial Cohesion (*Agenzia per la Coesione Territoriale*)—both operating under the Office of the Italian Presidency of the Council

of Ministers (PCM). The commissioned group identified those areas and thus developed a proper implementation strategy (UVAL, 2014). Marginal municipalities were identified according to their distance from hubs characterized by the presence of essential services:

- i) *education*, the presence of a diversified secondary educational level institute (*i.e.*, at least a high school and a technical-professional institute);
- ii) *healthcare*, the presence of a hospital with an emergency room and the capacity to handle complex emergencies, including resuscitation services (*i.e.*, emergency department and admission unit of at least first level);¹
- iii) *mobility*, the presence of a train station of at least silver category.²

Thus, the UVAL recognized the hub municipalities (*Poli* and *Poli-interurbani*)³ as those that offered all three services. Following this, the driving time (by car) from the closest hub represented the discriminant for the categorization of areas into four groups: belt (*Cintura*), intermediate (*Intermedio*), peripheral (*Periferico*), and ultra peripheral (*Ultraperiferico*). With the exclusion of the first category (belt), municipalities within the other three groups were considered to be Inner Areas. Distances were calculated from the centroids of the municipalities by considering the fastest route in the absence of traffic or road closures (*i.e.*, not real-time). The categorization was identified based on specific thresholds derived from the distribution of driving times for those municipalities: the median (20'), the third quartile (40'), and the 95th (75') percentile. The thresholds are synthesized in Figure 1 and the strategy identified Inner Areas as those municipalities more than 20 minutes away from an urban center (hub).

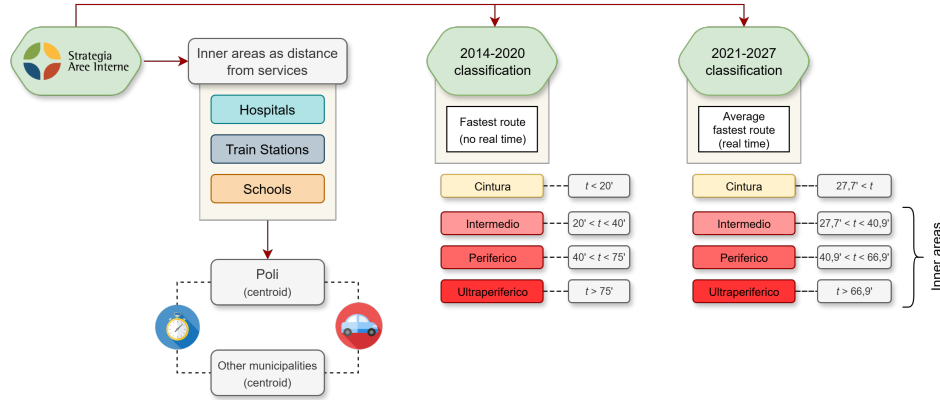
¹*Dipartimento d'Emergenza e Accettazione* (DEA).

²Category that includes two types of facilities: 1) medium/small stations and stops with significant usage (more than approximately 2,500 average passengers per day) and services for both long-distance and short-distance travel; 2) medium/small stations and stops with significant or high usage in the case of urban metro systems (in some cases more than 4,000 average passengers per day), often lacking a passenger building (*fabbricato viaggiatori*), unstaffed, and served only by regional/metropolitan services.

³Neighbouring municipalities capable of jointly offering the three essential services.

The first SNAI referred to the European Cohesion Policy programming period 2014–2020 and received funding from both national sources and European Structural and Investment Funds (ESIFs).⁴ The identification strategy developed by UVAL (2014) classified 4,261 municipalities as Inner Areas,⁵ but only 72 project areas—comprising 1,060 municipalities—were selected as pilot areas (*aree pilota*).⁶ These pilot areas corresponded to 13.2% of Italian municipalities, covering 17% of national territory and 3.5% of the population (as of 2014). Their selection followed a detailed assessment focusing on three main aspects: a high share of elderly residents (above 30%), the presence of younger cohorts, and the ability to attract immigration (Lucatelli, 2022). Participation also required effective cooperation among local institutions, primarily municipalities, which were grouped into project areas. Once selected, these areas signed specific framework agreements (*Accordi di Programma Quadro*) with regional and national authorities in order to receive funding (PCM, 2014).

Figure 1: *Identification of Inner Areas between different classification strategies*



⁴Within the ESIF framework, SNAI received funding from the European Regional Development Fund (ERDF), the European Social Fund (ESF), the European Agricultural Fund for Rural Development (EAFRD), and the European Maritime, Fisheries and Aquaculture Fund (EMFAF).

⁵Divided into 2,377 intermediate, 1,526 peripheral, and 358 ultra-peripheral municipalities.

⁶The distribution is as follows: 1 hub municipality (Orvieto, within the area named *Sud Ovest Orvietano*), 127 belt municipalities, 333 intermediate municipalities, 482 peripheral municipalities, and 117 ultra-peripheral municipalities. Because municipalities were organized into project areas, some belt municipalities were also included among the targeted units, while Orvieto remained the only hub municipality within the selected areas.

With the approach of the new funding period 2021–2027, the SNAI was revised starting in 2020 through a new identification strategy developed by a dedicated technical group (NUVAP, 2022). In particular, the number of hub municipalities was reconsidered in light of changes in the provision of essential services that followed the implementation of the European Fiscal Compact. The constitutionalization of the balanced budget constraint (Art. 81) extended fiscal discipline to all levels of public administration. Since the healthcare sector is managed at the regional level—and represents the largest expenditure item for regional governments—the spending review implemented after the sovereign debt crisis led to a rationalization of healthcare spending. This process resulted in a reduction in the supply of hospital services, primarily through the closure of several hospitals: at least 70 facilities have been shut down over the past decade (MSAL, 2025a). These changes provided a major rationale for revising the classification of Inner Areas, particularly in the context of increasing depopulation across marginal Italian municipalities.

The second SNAI referred to the subsequent funding period 2021–2027. In this case the new identification strategy, developed by NUVAP (2022), identified 123 different areas and a total of 1,904 municipalities,⁷ which correspond to 24.1% of total municipalities, 32.1% of Italian surface, and 7.7% of total population (as of 2020). Nonetheless, if we consider all municipalities whose distance from an urban center is greater than 27.7 minutes, the number of Inner Areas rises to 3,834 which corresponds to 48.5% of total municipalities, 58.8% of Italian surface, and 22.7% of total population (as of 2020).⁸ The confirmation of previous pilot areas and the identification of new target areas came from requests directly advanced by regions (PCM, 2022).

The second strategy was characterized not only by a revised number of hub municipalities, but also by an updated method for measuring distances.

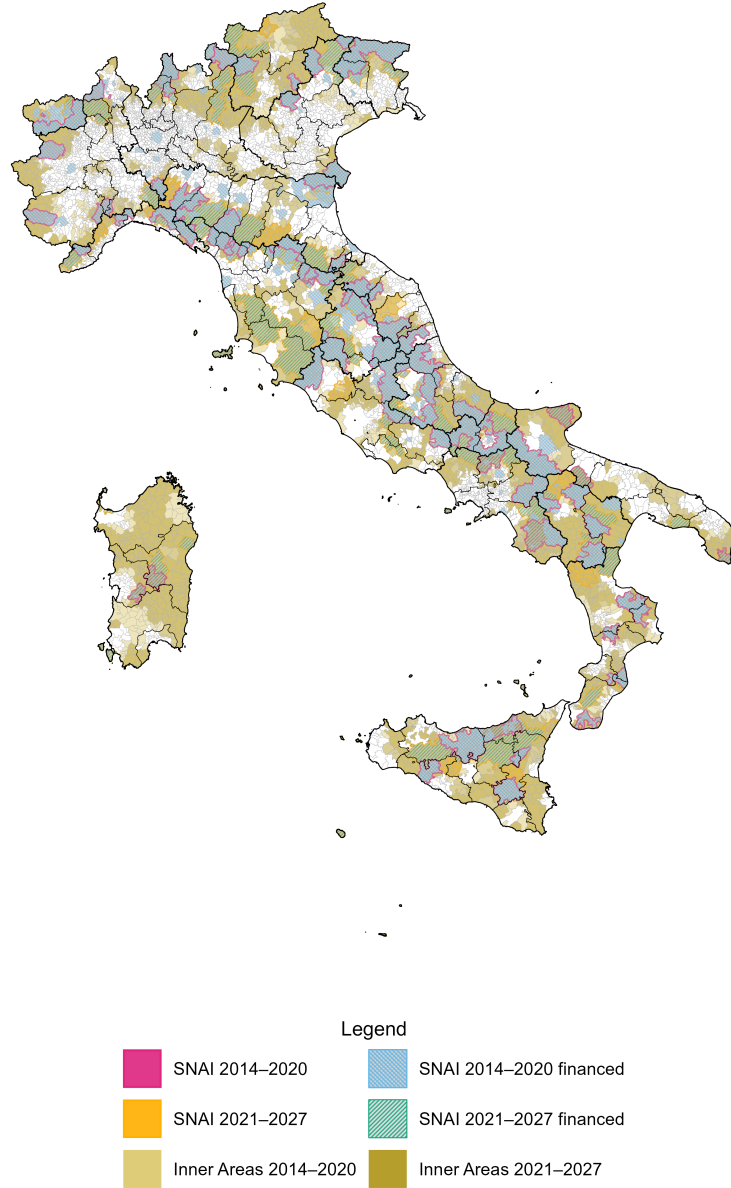
⁷Divided as 1 hub (Orvieto), 206 belt, 595 intermediate, 864 peripheral, and 238 ultra peripheral. To the 123 areas must be added 35 small islands.

⁸If we consider this broadest classification as well as those municipalities included in the 2021–2027 strategy but within the category of hub or belt, the number of Inner Areas rises to 4,040 municipalities which corresponds to 51.1% of total municipalities, 61.6% of Italian surface, and 23.6% of total population (as of 2020).

In particular, distances were calculated using Tom Tom routing data, thereby providing real-time estimates of travel times.⁹ Once the new driving times for each municipality were calculated, the identification of the Inner Areas threshold followed the same approach adopted in the first SNAI. Specifically, by considering the distribution of driving times, municipalities with values above the median were classified as marginal and therefore considered potential Inner Areas. The identification of hub municipalities remained unchanged, as it continued to rely on the simultaneous presence of the three essential services mentioned above. Figure 1 graphically summarizes the thresholds used in the SNAI 2021–2027 classification. As shown in the figure, the threshold used to identify marginal areas increased by almost eight minutes, shifting from 20 minutes to 27.7 minutes.

⁹Data has been downloaded for the sole working days of the week 14–20 October, 2019. In each day the download process has been launched in three different times (7:30, 8:30, and 9:30 am) resulting in 15 different distance-time observations for each municipality (to its corresponding closest hub) that have been eventually averaged to obtain a unique final value (ISTAT, 2022). Notice that this data has not been updated ever since; hence, official statistics are currently crystallized on data referred to late 2019 (NUVAP, 2022).

Figure 2: *Italian Inner Areas and municipalities receiving resources*



Notes: Financed municipalities for the 2014–2020 SNAI have been retrieved from [OpenCoesione](#) ([PCM, 2025](#)), data updated to February 28, 2025. We considered as funded all municipalities with at least one active project (even if not yet started). Financed municipalities for the 2021–2027 SNAI have been retrieved from the list provided by [PCM \(2023\)](#), updated to October 13, 2023. We considered as allegedly funded (eligible) the 37 confirmed areas of the 2014–2020 SNAI, the 30 re-perimetered areas, 43 (out of 56) of the new areas identified, and 35 small islands. Within the category of ‘Inner Areas 2014–2020’ and ‘Inner Areas 2021–2027’ we considered municipalities within the categories intermediate, peripheral, and ultra peripheral.

Sources: Authors’ personal elaboration based on [ISTAT \(2022, 2025a\)](#) and [PCM \(2023, 2025\)](#).

Overall resources allocated to Inner Areas amount to approximately € 1.76 billion, as reconstructed in Table A1 in the Appendix. These funds aim to support local development and improve the provision of essential services in marginal territories through integrated projects designed and implemented by local institutions. Resources are disbursed following the approval of specific framework agreements prepared by local authorities and approved by regional administrations and national coordination bodies. During the first programming cycle (2014–2020), resources amounted to € 281.2 million, while in the second cycle allocations increased to € 669 million. Additional resources include € 600 million from the Italian National Recovery and Resilience Plan (NRRP) and € 210 million from the Support Fund for marginal municipalities.

An important aspect to consider concerns the link between SNAI funding and the effective reduction of driving times to essential services. Although the entire strategy is conceptually built around accessibility and travel times (UVAL, 2014), the allocation of funds was not initially conditional on transport infrastructure improvements. In the first wave in particular, resources mainly supported local development projects such as heritage renovation, education initiatives, or incentives for local businesses (PCM, 2025). Only with the second wave of the strategy—the one evaluated in this study—did funding become more conditional and explicitly targeted at improving road safety and transport connections (see Table A1). This aspect should therefore be kept in mind both as a potential limitation of the SNAI and when interpreting the results of our analysis.

3.2 Updated distances from services: Inner Areas today

In this study, which focuses on travel times to essential services, we attempt to replicate the methodology adopted by NUVAP (2022) for the 2019 classification (ISTAT, 2022). To do so, we rely on two map data providers: OpenStreetMap (OSM) and Tom Tom. Both sources provide routing data; however, they differ in important ways. OSM is an open-access map database that calculates routes assuming normal road conditions, without accounting for real-time traffic or

temporary road closures. In contrast, Tom Tom provides routing data through a developer platform that incorporates real-time traffic information, similar to [Google Maps](#).¹⁰

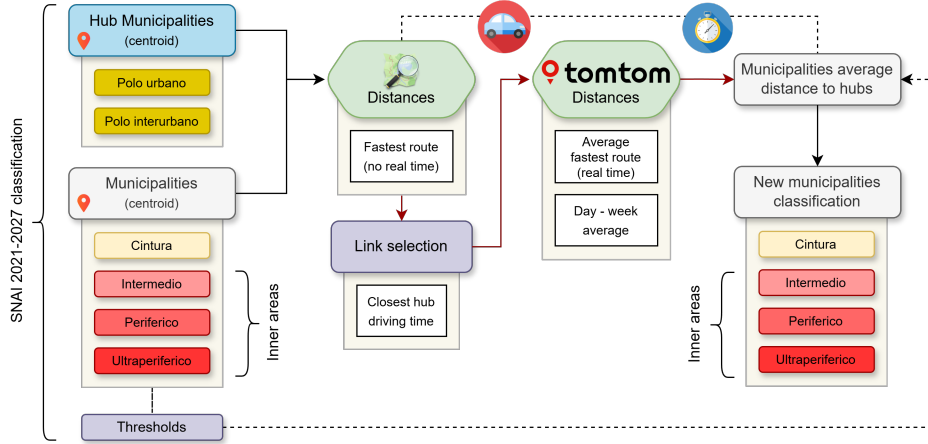
In the first step of our analysis, through OSM, we identified a distance matrix for each non-hub municipality to the closest hub.¹¹ Secondly, for each element of this matrix, we calculated the real time distance as the average of three daily queries¹² during the week spanning October 13 (Monday) to October 17 (Friday) of 2025. Notice that due to this selected time frame, we retrieved data for the corresponding week six years later of that used by ([NUVAP, 2022](#)) to perform the SNAI 2021–2027 classification in 2019. In this way, we obtained for each municipality a total of 15 time routes and calculated the average times. In this way, we were able to replicate as much as possible (with a scalable, replicable, and relatively low-cost approach) the methodology officially adopted to identify Inner Areas for the current SNAI 2021–2027. Henceforth, the final result represented an updated version of Inner Areas. The distribution of route driving times for OSM and Tom Tom sources are shown in [Figure 4](#) in comparison with data used by the SNAI 2021–2027 (values are expressed in natural logarithm for better graphic representation). We can clearly observe how after five years the distribution shifted to the right indicating a general increase of driving times to reach municipality hubs. The workflow adopted here is graphically synthesized in [Figure 3](#).

¹⁰Tom Tom was preferred to Google Maps for two main reasons: first, it is the data source used for the official identification of Inner Areas in the SNAI 2021–2027 classification; second, it offers more affordable developer plans.

¹¹We referred to the hub list provided by [PCM \(2023\)](#). Furthermore, we calculated each distance by considering centroids of each municipality.

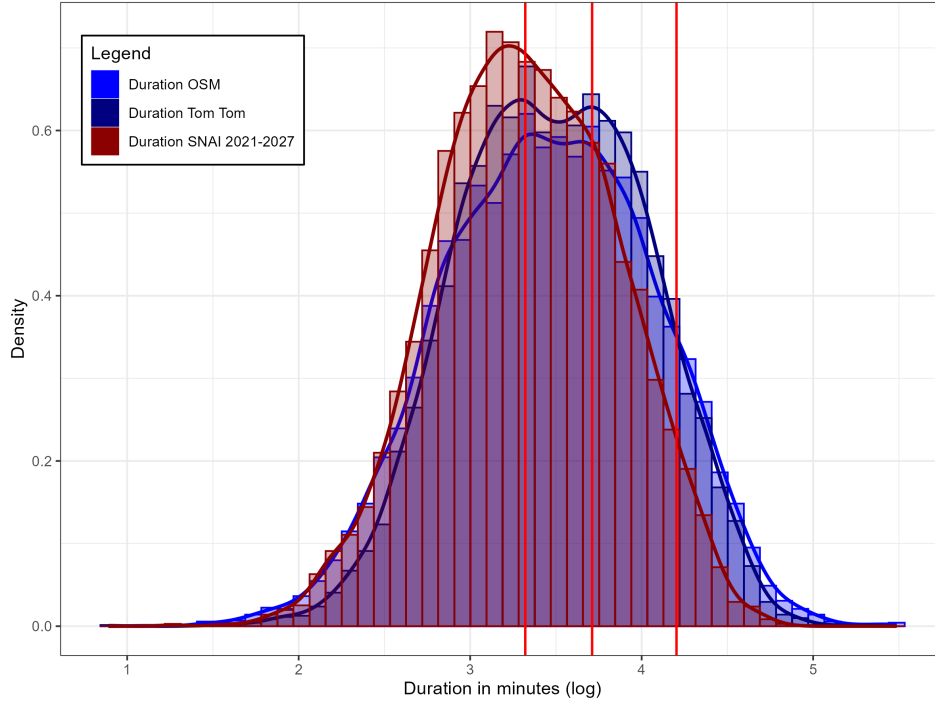
¹²We started queries at 7:00, 8:00, and 9:00 a.m. respectively, of each day. Because the developer API does not allow for bulk download, we had to run the queries (each query is a request to calculate the route data between two points) one at a time adding some delays between each one in order to avoid possible response errors. Therefore, each group of queries (equal to the number of municipalities, not hubs) required on average 8~9 hours to be finalized. Therefore, in order to avoid calculating the distances for each municipality always at the same time, in each group of queries we randomly selected the order of municipalities. We conducted the entire analysis in [R](#) by relying on the packages `osrm` and `tomtom` for OSM and Tom Tom data, respectively.

Figure 3: *Workflow for updating the Inner Areas classification*



The graphical representation of municipalities classified according to SNAI 2021–2027 and the updated version for 2025 with Tom Tom data is shown in Figure A1. In order to categorize classes we used the same thresholds adopted in the SNAI 2021–2027 classification. Based on our analysis, the total number of municipalities deemed to be Inner Areas in 2025 rises to 4,608, an increase of 20.2% with 775 additional municipalities. Therefore, 58.4% of Italian municipalities could potentially be ascribed as Inner Areas, 67.4% in terms of surface, and 28.2% in terms of population. The comparison between the two classifications is proposed also in terms of driving time with the scatter plot in Figure A2. Any deviation from the diagonal line would identify an increase (if over the line) or decrease (if below) of the updated classification compared to the previous one. Also, in this case, we can generally notice an increase in driving distances for most the municipalities, especially those classified as ultra peripheral in the last official classification. Furthermore, to better highlight the changes in Inner Areas the Appendix provides comparisons at regional level (Figures A3, A4, and A5).

Figure 4: *Distribution of driving distances from hubs, comparison between official data, OSM, and Tom Tom*

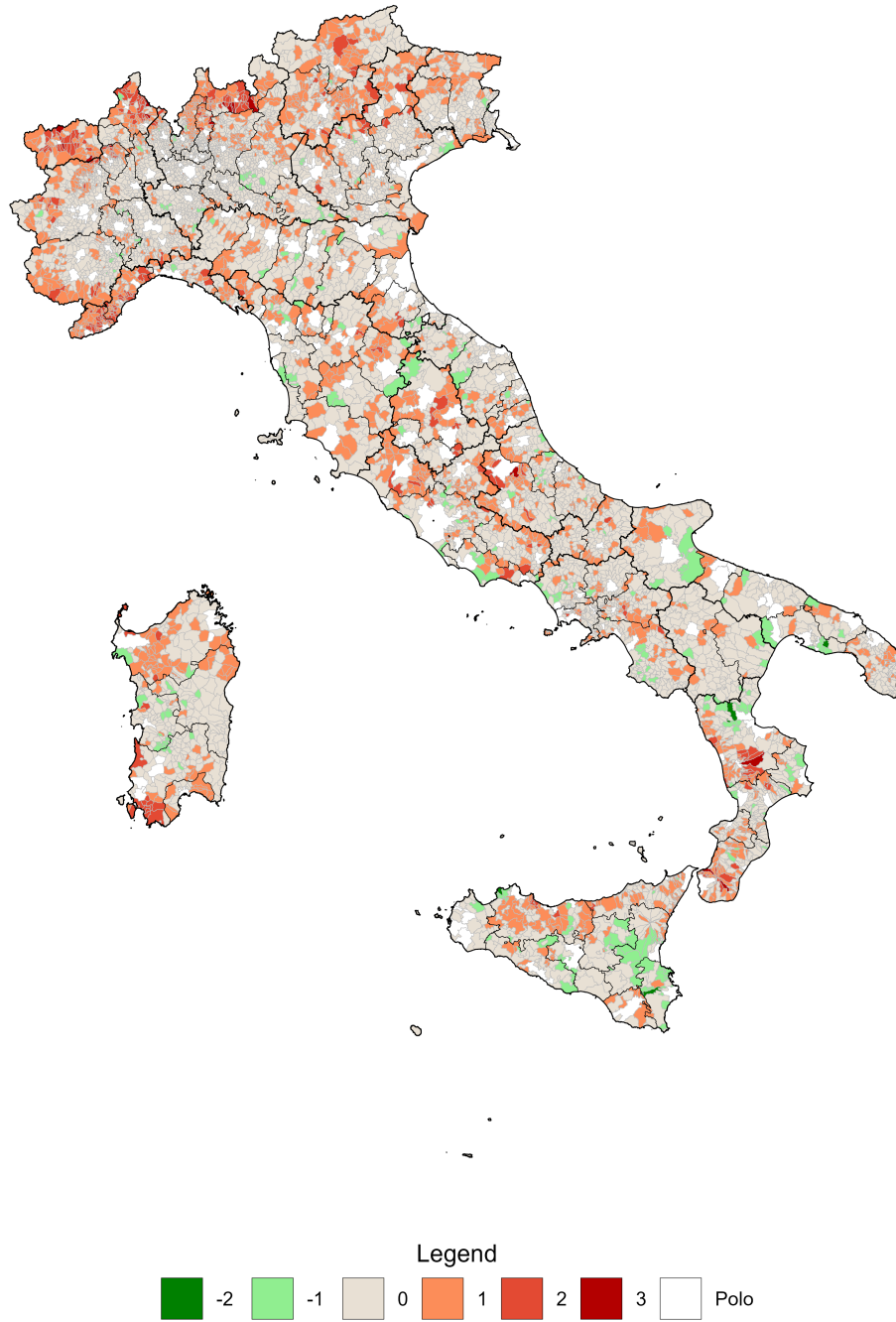


Notes: The vertical lines represent the thresholds identified by the 2021–2027 SNAI strategy to differentiate among Inner Areas. The first one from the left is the median, the second the third quartile while the third one the 95% percentile. For SNAI 2021-2027 these statistics are the following: 27.7, 40.9, and 66.9 minutes. For the OSM distribution these statistics are the following: 31.8, 49.2, and 83.4 minutes. For the Tom Tom distribution these statistics are the following: 32.6, 48.2, and 78.9 minutes.

Sources: Authors' personal elaboration based on [PCM \(2023\)](#).

In Figure 5 we can observe the category change for each non-hub municipality, from the class as identified in the SNAI 2021–2027 (year 2019) and the one we calculated for 2025. Negative values (in green) have to be interpreted in a positive way, meaning a general reduction in travel time, hence shifting from a more marginal class to a less marginal one. Positive values (in red) have to be interpreted instead in an opposite direction. For example, a municipality with a value of 3 would mean that it has either moved from belt to peripheral class or from intermediate to ultra peripheral. The sankey network in Figure A6 represents another graphical tool to better appreciate changes that occurred between the current classification (SNAI 2021–2027) and the updated one with 2025 Tom Tom data.

Figure 5: *Changes in area classification in 2025 compared to the SNAI 2021–2027 framework*



This initial result highlights the persistent marginalization of Inner Areas. Only a limited number of these municipalities have managed to reduce their distance from essential services, while others have experienced increasing isolation. At the same time, a potential ‘contagion’ effect appears to be spreading to municipalities that were not previously classified as marginal. This finding is consistent with the projections reported by [ISTAT \(2024\)](#), which indicate that over the next 20 years nearly 80% of Inner Area municipalities are expected to experience demographic decline, characterized by substantial outward migration, international emigration, and the outflow of young graduates.

The comparison of travel times between 2019 and 2025 can also be illustrated using box plots, where municipalities are grouped according to their SNAI 2021–2027 classification and whether they belong to the set of target municipalities (Figures [A7](#) and [A8](#) in the [Appendix](#)).

3.3 The dataset

The analysis focuses on all municipalities (with the exclusion of small islands) and comprises those within the 2021–2027 SNAI strategy as well as all municipalities identified as urban and interurban hubs. Therefore, the dataset comprises the following categories of municipalities: belt, intermediate, peripheral, and ultra peripheral. Consequently, the initial dataset comprises a total of 7,616 municipalities.^{[13](#)}

Our database has a panel structure covering two years, 2019 and 2025. The first year refers to the travel-time data identified by [NUVAP \(2022\)](#), while the second year corresponds to the updated classification described in [Section 3.2](#). Driving time constitutes the main outcome variable of our empirical model. Although the two waves originate from different data sources, our updating strategy seeks to replicate as closely as possible the original methodology developed by [NUVAP \(2022\)](#). Specifically, we rely on Tom Tom data collected during the same week and within the same time slots used in 2019, when

¹³We considered Italian administrative units as of January 1, 2025 which comprises a total of 7,896 municipalities ([ISTAT, 2025a](#)). Nonetheless, along the analysis that follows, the number of municipalities effectively employed is far lower.

driving times were first computed for the classification of Italian municipalities. We acknowledge the potential limitations of this approach. However, in the absence of officially updated data, our procedure represents a novel attempt to monitor changes in municipalities' distances from essential services.¹⁴

Nonetheless, we enriched the database with a set of data which we clustered into five major categories: *geographic*, *demographic*, *economics*, *institutional*, and *tourist-related* variables. Data for these covariates refer only to the year 2019 since it is the only year for which we relied on this data. Descriptive statistics of our database, which considers all municipalities classified as non-hub within the second SNAI strategy can be found in Table A2 in the Appendix.

In the first group of geographic variables we included surface (`sur`) and altitude (`alt`), retrieved from ISTAT (2025c).

Within the group of demographic variables, we included total population (`pop`), share of female (`pop_fem_per`) and foreign (`pop_for_per`) population. We also included the share of the population over 65 years old (`pop_65_per`) and the share of young individuals between 0 and 14 years old (`pop_14_per`) as well as the birth rate (`bir_rat`), and the total net migration (`net_mig`).

For the group of economic variables, we included both employment (`emp_rat`) and unemployment rates (`une_rat`) as well as taxation income (`tax_inc`) and entrepreneurship rate (`ent_rat`). All these variables have been retrieved from ISTAT (2024a).

Within the group of institutional variables, we relied on the Municipal Administrative Quality Index (MAQI) database developed by Cerqua *et al.* (2025). This index is divided into three pillars: i) quality and capacity of the bureaucracy (`ist_bur`); ii) quality of local politicians (`ist_pol`); iii) fiscal and economic performance (`ist_eco`).¹⁵ These indices ranges from 70 upwards to

¹⁴For instance, distance from essential services constitutes one component of the Italian municipal fragility index (ISTAT, 2024b). Although the index is currently available for multiple years (2018, 2019, 2021, and 2022), this specific sub-component remains unchanged over time, as it relies on the SNAI 2021–2027 classification developed by the NUVAP (2022).

¹⁵The first pillar refers to public employees and comprises the following variables: average years of education, number of bureaucrats per 1,000 inhabitants, average number of absences, and turnover rate. The second pillar refers to key political figures (*i.e.*, mayor, deputy mayor, members of the executive committee, and president of the local council) and comprises the

130 where higher values are associated with better institutional quality.

The last group of variables comprises those related to the touristic sector with the number of overnight stays for residents (`tou_ove_res`) and foreigners (`tou_ove_for`), respectively. All these variables have been retrieved from [ISTAT \(2025b\)](#).

3.4 The empirical strategy

To assess whether participation in the SNAI is associated with changes in proximity to essential services (closest hub), we employ a two-periods Difference-in-Differences (DiD) approach ([Cunningham, 2021](#)). We followed the generalized approach adopted by [Hansen \(2007\)](#), [Bertrand *et al.* \(2004\)](#), and [Atella *et al.* \(2023\)](#), but without using a continuous treatment specification. The estimating equation is the following (Eq. 1):

$$Y_{it} = \mu_i + \lambda_t + \gamma IA_{it} + \varepsilon_{it} \quad (1)$$

where i indexes municipalities and t refers to the years 2019 and 2025. The variables are defined as follows:

- Y_{it} is the outcome variable, measuring driving time in minutes from the municipality centroid to the centroid of the closest hub. For $t = 2019$, we rely on the official distances provided by [PCM \(2023\)](#), while for $t = 2025$ we recalculate the indicator as described in Section 3.2;
- μ_i denotes municipality fixed effects, which absorb time-invariant unobserved heterogeneity at the local level;
- λ_t represents time fixed effects, capturing shocks common to all municipalities;

following variables: average years of education, gender balance index, and share of white collar workers. The third pillar, which refers to the local government, comprises the following variables: spending rigidity, spending capacity, collection capacity, and share of municipal budget for investments ([Cerqua *et al.*, 2025](#)).

- IA_{it} is a dummy variable equal to 1 if municipality belongs to a SNAI project area and 0 otherwise;
- γ is the coefficient of interest, capturing the effect of being part of SNAI;
- ε_{it} represents the idiosyncratic error term of the model.

This empirical setting presents several limitations, which we address through a series of methodological choices.

A first concern relates to treatment assignment. Within the DiD framework, identification would require the selection of SNAI municipalities to be unrelated to unobserved changes in municipal driving times (Besley and Case, 2000; Heckman, 2000). This assumption is demanding in the present setting because distance from essential services is itself one of the criteria used to classify Inner Areas. As illustrated in Figures A7 and A8, target municipalities generally exhibit higher driving times than non-target municipalities. However, this pattern does not hold uniformly across all marginality classes: among ultra-peripheral municipalities, non-target municipalities display slightly higher driving times.

At the same time, the designation of project areas is not mechanically determined by driving time alone. The selection of treated areas results from an institutional process involving applications submitted by Italian regions and autonomous provinces under the guidelines of the Italian Partnership Agreement 2021–2027 (PCM, 2022). The agreement specifies several criteria for the identification of project areas, including continuity with the previous SNAI 2014–2020 cycle, priority for peripheral and ultra-peripheral territories, the presence of severe demographic, economic, social, or environmental challenges, the willingness of municipalities to cooperate through inter-municipal arrangements, and the avoidance of excessively large territorial units. Therefore, although distance from essential services plays a central role in the classification process, treatment assignment depends on multiple institutional and territorial factors. This weakens the idea of purely mechanical selection, but it does not eliminate endogeneity concerns. For this reason, the estimates reported below should be interpreted with caution.

For the identification of control units, we initially restrict the sample to municipalities classified as Inner Areas under the SNAI 2021–2027 classification. In a secondary specification, we relax this restriction by also including belt municipalities. The initial dataset therefore comprises 3,801 municipalities, of which 1,525 are classified as treated.

In our empirical setting, all municipalities identified as target areas under the SNAI 2021–2027 are considered treated. This choice reflects an important data limitation: the monitoring system for SNAI funding does not provide comprehensive information on the effective allocation of resources in the current programming cycle. Institutional changes in the governance of the strategy have further complicated the availability of consistent monitoring data.¹⁶

As already stated in Section 3.1, a total of € 1.76 billion has been allocated to the SNAI, most of which is devoted to the second programming cycle - the focus of our analysis. Within these resources, part of the funding is explicitly earmarked for improving road accessibility and safety in Inner Areas (approximately € 300 million). However, the government monitoring system for cohesion policies ([OpenCoesione](#)) provides a dedicated SNAI category only for the 2014–2020 cycle, reporting € 540.4 million across 2,422 projects as of February 28, 2025 ([PCM, 2025](#)). For the subsequent 2021–2027 cycle, a specific SNAI monitoring category is no longer available.¹⁷ Due to this limitation, treatment is defined on the basis of eligibility rather than observed funding intensity. To mitigate potential bias, municipalities that had already received SNAI funds before 2019 are excluded from the analysis. After removing these already-treated units, the final sample comprises 3,032 municipalities, of which 837 are treated.

A second limitation concerns the time structure of the data. Because com-

¹⁶The SNAI 2021–2027 strategy was initially coordinated by the Agency for Territorial Cohesion (*Agenzia per la Coesione Territoriale*) under the Presidency of the Council of Ministers. Following institutional reforms in 2023, responsibility was transferred to the Department for Cohesion Policies and the South (*Dipartimento per le Politiche di Coesione e per il Sud*).

¹⁷A search within the OpenCoesione database for the 2021–2027 programming period using the terms “aree interne”, “snai”, and “strategia nazionale aree interne” identifies only three projects loosely related to Inner Areas.

parable retrospective information on driving times is not available for multiple years, the empirical analysis relies on only two observation periods (2019 and 2025). This constraint prevents the implementation of a staggered treatment design and makes the parallel-trends assumption untestable in the standard way. It also implies that the analysis cannot include placebo DiD estimates based on earlier driving-time waves. Nevertheless, the structure of SNAI funding, which typically involves substantial delays between allocation and implementation, suggests that the five-year interval between policy initiation (2020) and the second observation period (2025) is sufficiently long for eligible municipalities to have experienced some degree of treatment exposure.

Given the substantial heterogeneity across municipalities, we complement the DiD specification with a Propensity Score Matching (PSM) procedure (Rosenbaum and Rubin, 1983, 1985) prior to estimation. The objective of matching is to improve comparability between treated and control municipalities by balancing pre-treatment observable characteristics. In this sense, PSM does not fully solve the endogeneity of treatment assignment, but it helps restrict the comparison to municipalities that are more similar in terms of observed characteristics. The propensity score is defined as follows (Eq. 2):

$$p(X) = \text{Prob}(IA = 1 \mid X_i) = E(IA \mid X) \quad (2)$$

where $X = (X^1, \dots, X^k)$ denotes the vector of covariates described in Section 3.3. These variables capture geographic, demographic, economic, institutional, and tourism-related characteristics. Importantly, the matching procedure is based only on pre-treatment covariates.¹⁸

We estimate four alternative matching specifications using generalized linear models with both *logit* and *probit* link functions, with and without caliper restrictions (Althausen and Rubin, 1970). Following Rosenbaum and Rubin (1985), the caliper width is set at 0.25 standard deviations of the propensity score. Matching is implemented using a 1 : k nearest-neighbor design with

¹⁸In the Appendix we provided descriptive statistics of this sample, before and after PSM, divided between treated and control units (Tables A3 and A4).

$k = 3$, meaning that each treated municipality is matched with up to three control municipalities with the closest propensity scores (Rassen *et al.*, 2012). The preferred specification is selected on the basis of the lowest standardized mean difference (SMD) across covariates. In our case, the selected model is the probit specification without caliper.¹⁹

After matching, all 807 treated municipalities are successfully paired with comparable control units, while 44 control municipalities are discarded. The final matched sample is slightly smaller because of missing values in some covariates. Post-matching diagnostics indicate satisfactory covariate balance, with SMD values below the conventional 0.1 threshold (Stuart and Rubin, 2008). Balance diagnostics and graphical assessments of the propensity score distributions are reported in the Appendix. In particular, Figure A12 reports the love plot comparing SMD values before and after matching, while Figure A13 shows the distribution of propensity scores in the two groups. We also report the box plot for driving time in treated and control municipalities after matching (Figure A9) and a map of the municipalities included in the matched sample (Figure A10).

Overall, the empirical strategy should be interpreted cautiously. The combination of a two-period DiD framework and matching-based comparability checks provides useful evidence on the relationship between SNAI participation and changes in accessibility to service hubs, but it does not fully remove concerns related to non-random treatment assignment and the absence of multiple pre-treatment periods. For this reason, the estimates can also be read more conservatively as descriptive panel associations rather than as definitive causal effects.

4 Results and discussion

In the baseline specification, we evaluate the association between SNAI participation and changes in driving time for municipalities targeted by the strategy. Specifically, we compare driving times observed in 2019 with those calculated

¹⁹The matching procedure was performed using the R package `MatchIt`.

for 2025, focusing on municipalities involved in the second wave of the SNAI. As discussed previously, the analysis includes only municipalities classified as Inner Areas (*i.e.*, municipalities whose driving time to the closest hub in 2019 exceeded 27.7 minutes) and excludes municipalities that had already received funding under the first SNAI programming cycle before 2019.

Because driving times depend on the configuration of transport networks shared across neighboring municipalities, the possibility of spatial spillovers cannot be ruled out. Improvements or deteriorations in the road network of one municipality may affect accessibility conditions in nearby municipalities, potentially violating the Stable Unit Treatment Value Assumption (SUTVA). In addition, spatial correlation in unobserved shocks affecting road infrastructure could lead to correlated error terms across neighboring units. To account for these issues, we report standard errors clustered at the province level. Despite the partial institutional reform introduced by Law 56/2014, Italian provinces continue to retain significant responsibilities for the management and maintenance of the provincial road network. Consequently, clustering at the province level provides a reasonable approximation for capturing spatially correlated shocks in transport infrastructure conditions.

Furthermore, given the well-documented territorial divide between Northern/Central Italy and the Southern regions (*Mezzogiorno*) (Fratesi and Percoco, 2014; Mauro *et al.*, 2023), and considering that a large share of Inner Areas are located in Southern Italy, we also perform a separate analysis distinguishing between Center-North and Southern municipalities. Following Bucci *et al.* (2024), we group regions accordingly.²⁰ In both subsamples we perform Propensity Score Matching prior to estimating the DiD model.²¹ As in the full sample, post-matching diagnostics indicate satisfactory covariate balance (see Figures A14–A19 in the Appendix).

²⁰Northern and Central regions include: Aosta Valley, Emilia-Romagna, Friuli Venezia Giulia, Lazio, Liguria, Lombardy, Marche, Piedmont, Trentino-Alto Adige, Tuscany, Umbria, and Veneto. Southern regions include: Abruzzo, Apulia, Basilicata, Calabria, Campania, Molise, Sardinia, and Sicily.

²¹Central regions are grouped together with Northern regions due to the limited number of municipalities in these areas. Splitting the sample further would have substantially reduced the number of observations available after matching.

The main results are reported in Figure 1. On average, municipalities targeted by the SNAI are associated with an increase in driving time of approximately 2.4 minutes relative to comparable Inner Area municipalities not included in the strategy. This result suggests a modest deterioration in accessibility for treated municipalities over the period considered. Although an increase of approximately two and a half minutes may appear limited in absolute terms, it should be interpreted in the context of already remote territories where accessibility constraints are substantial.

In particular, access to healthcare services represents a critical dimension of territorial inequality. Within the Essential Levels of Care (*Livelli Essenziali di Assistenza* – LEA) of the Italian National Health Service (NHS), specific performance targets are defined for emergency response times. For example, the recommended ambulance response time for conditions such as myocardial infarction is set at approximately 18 minutes (District Assistance area: D09Z, Alarm-to-Target Interval) (MSAL, 2025b). In this context, even relatively small increases in travel time may have non-negligible implications for emergency healthcare accessibility in highly marginal areas.

When the sample is divided between Northern–Central and Southern regions, the estimated coefficients remain positive and display a somewhat larger magnitude in the Northern–Central group. However, in both subsamples the coefficients are not statistically significant at conventional levels. This suggests that the association between SNAI participation and changes in driving time does not differ systematically across the two macro-regions.

Table 1: *Effect of SNAI on municipalities' driving time from essential services, 2021–2027 strategy*

	All	North-Center	South
	(1)	(2)	(3)
did	2.422** (1.141)	2.219 (1.667)	0.304 (1.149)
Number of municipalities	2,810	1,144	985
Treated municipalities	807	372	345
Observations	5,620	2,288	1,970

Significance codes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Notes: Robust standard errors clustered at the provincial level.

One possible explanation for the negative association observed in the baseline results relates to a potential crowding-out effect associated with the allocation of SNAI resources. In several cases, SNAI funding has been characterized by relatively weak conditionality regarding the specific type of interventions to be implemented. Although the identification of Inner Areas is primarily based on their distance from essential services, the design and implementation of projects involve local policymakers and organizations, which may prioritize more immediate local needs. As a result, resources may have been directed toward initiatives such as the promotion of cultural activities or the renovation of historical assets rather than investments aimed at improving road accessibility. At the same time, Italian municipalities are formally responsible for several fundamental functions under national legislation (D.L. 95/2012), including urban and spatial planning at the municipal level, participation in supra-municipal territorial planning, and the organization of local public services of general interest, such as municipal transport services. These responsibilities imply a role in the management and maintenance of road infrastructure within their jurisdiction. Nevertheless, if SNAI resources were partially redirected toward other local priorities, the resulting displacement of investments in transport infrastructure could have contributed to the limited improvements in accessibility observed in the data. In recognition of these issues, more recent SNAI allocations introduced a partial conditionality in the use of funds.

In particular, a portion of the resources has been explicitly earmarked for improving road accessibility in Inner Areas, amounting to approximately € 350 million (Table A1).

In a second specification, we relax the initial restriction that limited the sample to municipalities classified as Inner Areas under the SNAI 2021–2027 classification by also including municipalities categorized as belt areas. The empirical strategy remains unchanged: municipalities that had already received funding under the SNAI 2014–2020 cycle are excluded from the analysis, and a PSM procedure is implemented to balance treated and control units.²²

Results, reported in Figure 2, show that the estimated coefficient remains positive and statistically significant when the full sample of municipalities is considered. In this specification, treated municipalities require on average approximately 2.6 additional minutes to reach the closest hub compared with matched control municipalities. Therefore, when belt municipalities are also included in the analysis, Inner Areas targeted by the policy display a slightly larger increase in driving time. Consistent with the baseline specification, there is no clear evidence of regional heterogeneity. For Northern–Central municipalities, the estimated coefficient remains positive, while it becomes slightly negative for Southern municipalities; however, in both cases the estimates are not statistically significant.

²²Descriptive statistics before and after PSM are reported in Tables A5 and A6, while Figures A22–A30 present balancing diagnostics for the three analyzed clusters. In addition, Figure A20 compares the distribution of driving times after PSM across municipality groups, while Figure A21 illustrates the spatial distribution of treated and control units.

Table 2: *Effect of SNAI on municipalities' driving time from essential services, 2021–2027 strategy*

	All	North-Center	South
	(1)	(2)	(3)
did	2.617** (1.022)	0.560 (1.650)	−0.213 (1.317)
Number of municipalities	5,322	1,508	1,122
Treated municipalities	887	450	376
Observations	10,644	3,016	2,244

Significance codes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Notes: Robust standard errors clustered at the provincial level.

4.1 Limitations and future developments

This study presents several limitations that should be considered when interpreting the findings. First, the empirical design relies on a two-period DiD framework (2019 and 2025), which prevents the implementation of conventional pre-trend tests. Consequently, the parallel-trends assumption cannot be directly verified. Although the analysis combines DiD with PSM in order to improve comparability between treated and control municipalities, the estimates should still be interpreted cautiously, as treatment assignment is not fully exogenous and may remain partially correlated with underlying territorial characteristics.

A second limitation concerns the monitoring of SNAI funding. Due to the lack of detailed information in the monitoring system for the 2021–2027 programming cycle, it was not possible to identify precisely which municipalities effectively received funding or which specific interventions were implemented. As a result, treatment is defined on the basis of eligibility rather than observed funding intensity. This limitation restricts our ability to analyze the intensive margin of the policy and may attenuate the estimated effects, since municipalities classified as treated may have received different amounts of resources or may not yet have implemented projects.

Another factor potentially affecting the results is the presence of concurrent infrastructure investments financed through other European programs, particu-

larly the Italian NRRP. Furthermore, we can also consider road works linked to the Winter Olympic games hosted by the Italian cities of Milan and Cortina between February and March 2026. Large-scale roadworks and infrastructure upgrades may temporarily increase travel times due to road closures, diversions, or construction-related disruptions. These short-term effects could lead to a temporary overestimation of driving times in certain areas, thereby masking longer-term improvements in accessibility.

The analysis focuses exclusively on driving times by private car. This choice ensures consistency with the methodology used in the SNAI 2021–2027 classification, which also relies on road travel times. Nevertheless, accessibility conditions may also depend on the availability and quality of public transport services. The Tom Tom dataset used in this study does not provide information on travel times by public transport. Alternative data sources, such as the Google Maps API or multimodal transport datasets, could allow future research to incorporate public transport accessibility and provide a more comprehensive measure of territorial connectivity.

In addition, the relationship between SNAI interventions and reductions in travel times is not necessarily direct. While distance from essential services constitutes a key element in the identification of Inner Areas, many SNAI projects target different policy objectives, including the enhancement of cultural heritage, the promotion of tourism, or the strengthening of local services. Consequently, local policymakers may prioritize investments aimed at improving services within municipalities rather than reducing travel times to external hubs.

Recent policy developments partly address this issue. The Italian government has increasingly focused on strengthening intermediate healthcare infrastructures, including community hospitals, community houses, and territorial operations centers. These initiatives involve nearly € 3.3 billion from the NRRP and more than 2,700 projects.²³ However, the current SNAI classifi-

²³The NRRP includes 427 projects for community hospitals (€ 1 billion), 1,415 projects for community houses (€ 2 billion), and 867 projects for territorial operations centers (€ 280 million) ([Fondazione Openpolis, 2025](#)).

cation continues to rely on traditional hospital hubs and does not explicitly account for these new intermediate facilities.

Future research could build on this work in several directions. First, improved monitoring of SNAI implementation would allow researchers to measure treatment intensity and distinguish between different types of interventions. Second, accessibility measures could be refined by calculating travel times from municipalities to the actual locations of specific services, such as hospitals, schools, or railway stations, rather than relying solely on hub centroids. Finally, expanding the temporal dimension of the dataset would make it possible to test pre-treatment trends and apply more advanced causal inference methods, thereby strengthening the identification of policy effects.

Taken together, these limitations suggest that the results should be interpreted primarily as evidence on the association between SNAI participation and changes in accessibility, rather than as definitive causal estimates of the policy’s impact.

5 Conclusions

A decade after its launch, the Italian National Strategy for Inner Areas (SNAI) shows mixed evidence with respect to one of its central objectives: improving accessibility to essential services in peripheral municipalities. By developing a novel and replicable framework based on real-time travel data from OpenStreetMap (OSM) and Tom Tom, this study provides updated evidence on the geography of territorial marginality in Italy and examines the relationship between participation in the strategy and changes in accessibility.

The empirical results suggest that municipalities targeted by the SNAI did not experience measurable improvements in accessibility during the period considered. On average, treated municipalities display a modest increase in travel times to service hubs relative to comparable municipalities not included in the strategy. Although the magnitude of the effect is relatively small in absolute terms, the results point to a persistence—and in some cases a slight worsening—of accessibility conditions in already remote territories. The

updated classification of Inner Areas for 2025 also indicates a broader expansion of territorial marginality, suggesting that infrastructure gaps remain substantial.

These findings should be interpreted with caution: treatment assignment is partly related to territorial characteristics and the analysis relies on a two-period framework, which limits the possibility of testing pre-treatment dynamics. Moreover, SNAI interventions encompass a wide range of policy objectives, many of which are not directly linked to improvements in transport infrastructure.

Nevertheless, the evidence highlights the importance of aligning place-based development strategies more closely with measurable accessibility outcomes. While the SNAI may contribute to other objectives, such as strengthening local services, cultural initiatives, or social cohesion, its ability to reduce spatial isolation appears limited in the short run. Future cohesion policies could benefit from stronger monitoring systems, clearer conditionality in infrastructure investments, and more precise measurement of accessibility conditions. Improving the spatial targeting and evaluation of territorial policies will be crucial to ensure tangible improvements in the everyday lives of residents in Italy's most fragile regions.

References

- Adamiak, C., Rodríguez-Pose, A., Churski, P., Dubownik, A., Pietrzykowski, M., Szyda, B., and Rosik, P. (2024). Places that matter and places that don't: territorial revenge and counter-revenge in Poland. *Territory, Politics, Governance*, pages 1–26.
- Akee, R., Jones, M. R., and Simeonova, E. (2025). Place Based Economic Development and Tribal Casinos. National Bureau of Economic Research.
- Althausen, R. P. and Rubin, D. (1970). The computerized construction of a matched sample. *American Journal of Sociology*, 76(2):325–346.
- ANCT (2025). France ruralités. Agence Nationale de la Cohésion des Territoires. Retrieved from: <https://anct.gouv.fr/programmes-dispositifs/france-ruralites> [Accessed May 28, 2025].
- Atella, V., Braione, M., Ferrara, G., and Resce, G. (2023). Cohesion Policy Funds and local government autonomy: Evidence from Italian municipalities. *Socio-Economic Planning Sciences*, 87:101586.
- Barca, F. (2009). An Agenda for a Reformed Cohesion Policy. A place-based approach to meeting European Union challenges and expectations. Technical report, European Parliament.
- Barca, F. (2019). Place-based policy and politics. *Renewal: A Journal of Social Democracy*, 27(1):84–95.
- Barca, F., McCann, P., and Rodríguez-Pose, A. (2012). The case for regional development intervention: place-based versus place-neutral approaches. *Journal of regional science*, 52(1):134–152.
- Benassi, F., Tomassini, C., and Lallo, C. (2024). The local regression approach as a tool to improve place-based policies: The case of Molise (Southern Italy). *Spatial Demography*, 12(2):2.

- Bertolini, P. and Pagliacci, F. (2017). Quality of life and territorial imbalances. A focus on Italian inner and rural areas. *Bio-based and Applied Economics*, 6(2):183–208.
- Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.
- Besley, T. and Case, A. (2000). Unnatural experiments? Estimating the incidence of endogenous policies. *The Economic Journal*, 110(467):672–694.
- Bolzoni, M., Cotella, G., and Brovarone, E. V. (2026). Repopulating peripheral rural areas? The approach of the Italian National Strategy for Inner Areas. *Journal of Rural Studies*, 122:103971.
- Bucci, V., Ferrara, G., and Resce, G. (2024). Female presence in local government and cost efficiency: the case of Italian municipalities. *Regional Studies*, 58(1):16–29.
- Busso, M., Gregory, J., and Kline, P. (2013). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review*, 103(2):897–947.
- CdD (2023). La Strategia Nazionale per le Aree Interne (SNAI) e il Fondo di sostegno per i comuni marginali. Technical report, Camera dei Deputati. Servizio Studi.
- Cerqua, A., Giannantoni, C., Zampollo, F., and Mazziotta, M. (2025). The municipal administration quality index: the Italian case. *Social Indicators Research*, pages 1–34.
- Compagnucci, F. and Morettini, G. (2024). Inner areas matter: A place-sensitive approach for the identification of the Daily Life Spaces in the Italian Abruzzo region. *Socio-Economic Planning Sciences*, 93:101859.
- Cotella, G. and Brovarone, E. V. (2020). The Italian national strategy for inner areas: A place-based approach to regional development. In Bański, J.,

- editor, *Dilemmas of regional and local development*, chapter 3, pages 50–71. Routledge, London, UK.
- Cunningham, S. (2021). *Causal inference: The mixtape*. Yale university press, New Haven, CT-US.
- de Vega Perancho, R. M., Díaz-Dapena, A., and Viñuela, A. (2025). The multidimensional phenomenon of left behindness: A local approach. *Regional Science Policy & Practice*, page 100232.
- Di Matteo, D. (2025). Regional implications of the Italian inner areas strategy. *Regional Studies*, pages 1–16.
- Duranton, G. and Venables, A. J. (2018). Place-based policies for development. National Bureau of Economic Research Working Paper, n. 24562.
- Fondazione Openpolis (2025). Open PNRR. Retrieved from: <https://openpnrr.it/> [Accessed May 23, 2025].
- Fratesi, U. and Percoco, M. (2014). Selective migration, regional growth and convergence: Evidence from Italy. *Regional Studies*, 48(10):1650–1668.
- Gallo, G. and Pagliacci, F. (2020). Widening the gap: the influence of ‘inner areas’ on income inequality in Italy. *Economia Politica*, 37(1):197–221.
- Guzzardi, D. and Morelli, S. (2024). A new geography of inequality: Top incomes in italian regions and inner areas. Technical report, Laboratory of Economics and Management (LEM), Sant’Anna School of Advanced Studies. LEM Working Paper Series, No. 2024/16.
- Hansen, C. B. (2007). Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. *Journal of econometrics*, 140(2):670–694.
- Heckman, J. J. (2000). Causal parameters and policy analysis in economics: A twentieth century retrospective. *The Quarterly Journal of Economics*, 115(1):45–97.

- Iammarino, S., Rodriguez-Pose, A., and Storper, M. (2019). Regional inequality in Europe: evidence, theory and policy implications. *Journal of economic geography*, 19(2):273–298.
- ISTAT (2022). Classificazioni dei Comuni secondo le caratteristiche di Area Interna (geografia amministrativa al 30 settembre 2020) . Istituto Nazionale di Statistica. Retrieved from: https://www.istat.it/wp-content/uploads/2022/07/20220715_Elenco_Comuni_Classi_di_Aree_Interne.xlsx [Accessed December 11, 2025].
- ISTAT (2022). La geografia delle aree interne nel 2020: vasti territori tra potenzialità e debolezze. Istituto Nazionale di Statistica. Statistiche Focus, July 20, 2022.
- ISTAT (2024a). A misura di comune. Istituto Nazionale di Statistica. Retrieved from: <https://www.istat.it/statistica-sperimentale/aggiornamento-degli-indicatori-del-sistema-informativo-a-misura-di-comune/> [Accessed May 8, 2025].
- ISTAT (2024b). Indice di fragilità comunale (IFC). Istituto Nazionale di Statistica. Retrieved from: https://esploradati.istat.it/databrowser/#/it/dw/categories/IT1,Z0930TER,1.0/CFI_MUN [Accessed May 21, 2025].
- ISTAT (2024). La demografia delle aree interne: dinamiche recenti e prospettive future. Istituto Nazionale di Statistica. Statistiche Focus, July 29, 2024.
- ISTAT (2025a). Confini delle unità amministrative a fini statistici. Istituto Nazionale di Statistica. Retrieved from: <https://www.istat.it/notizia/confini-delle-unita-amministrative-a-fini-statistici-al-1-gennaio-2018-2/> [Accessed May 16, 2025].
- ISTAT (2025b). Movimento dei clienti (arrivi e presenze) negli esercizi ricettivi per tipologia ricettiva, residenza dei clienti e comune di destinazione. Istituto Nazionale di Statistica. Retrieved from: <https://esploradati.istat.it/databrowser/#/it/dw/categories/>

- [IT1,Z0700SER,1.0/SER_TOURISM/SER_TOURISM_RELATED_FILES](#) [Accessed September 11, 2025].
- ISTAT (2025c). Principali statistiche geografiche sui comuni. Istituto Nazionale di Statistica. Retrieved from: <https://www.istat.it/classificazione/principali-statistiche-geografiche-sui-comuni/> [Accessed May 16, 2025].
- Lucatelli, S. (2022). La Snai nel contesto delle politiche di sviluppo e coesione. In Lucatelli, S., Luisi, D., and Tantillo, F., editors, *L'Italia lontana. Una politica per le aree interne*, chapter 1, pages 37–91. Donzelli Editore, Rome, IT.
- Mastronardi, L., Giannelli, A., and Romagnoli, L. (2021). Detecting the land use of ancient transhumance routes (Tratturi) and their potential for Italian inner areas' growth. *Land use policy*, 109:105695.
- Mastronardi, L. and Romagnoli, L. (2020). Community-based cooperatives: A new business model for the development of Italian inner areas. *Sustainability*, 12(5):2082.
- Mauro, L., Pigliaru, F., and Carmeci, G. (2023). Decentralization, social capital, and regional growth: The case of the Italian North-South divide. *European Journal of Political Economy*, 78:102363.
- Modica, M., Urso, G., and Faggian, A. (2021). Do «Inner Areas» Matter? Conceptualization, trends and strategies for their future development path. *Scienze Regionali*, 20(2):237–265.
- Monturano, G., Resce, G., and Ventura, M. (2025). Short-term Impact of Financial Support to Inner Areas. *Italian Economic Journal*, pages 1–40.
- Moscarelli, R. and Fera, A. (2024). La Strategia Nazionale Aree Interne 10 anni dopo: una proposta di analisi comparativa tra le programmazioni 2014-2020 e 2021-2027. *Scienze Regionali*, 24(1):101–120.

- MSAL (2025a). Annuario Statistico del Servizio Sanitario Nazionale. Assetto organizzativo, attività e fattori produttivi del SSN. Anno 2023. Technical report, Ministero della Salute.
- MSAL (2025b). Monitoraggio dei LEA attraverso il Nuovo Sistema di Garanzia. Relazione 2023. Technical report, Ministero della Salute.
- Nakajima, H. and Murayama, A. (2024). Inclusive urban regeneration approaches through small projects: A comparative study of three Japanese machizukuri cases. *Cities*, 152:105241.
- Neumark, D. and Simpson, H. (2015). Place-based policies. In Duranton, G., Henderson, J. V., and Strange, W. C., editors, *Handbook of regional and urban economics*, volume 5, chapter 18, pages 1197–1287. Elsevier.
- NUVAP (2022). Aggiornamento 2020 della Mappa delle Aree Interne. Technical report, Nucleo di Valutazione e Analisi per la Programmazione.
- Partridge, M. D., Rickman, D. S., Olfert, M. R., and Tan, Y. (2018). When spatial equilibrium fails: Is place-based policy second best? *Regional Studies*, 49:1303–1325.
- PCM (2014). Accordo di Partenariato 2014-2020 Italia. Technical report, Presidenza del Consiglio dei Ministri, Dipartimento per le Politiche di Coesione.
- PCM (2022). Accordo di Partenariato 2021-2027 Italia. Technical report, Presidenza del Consiglio dei Ministri, Dipartimento per le Politiche di Coesione.
- PCM (2023). Elenco Aree SNAI 2021-2027. Presidenza del Consiglio dei Ministri: Dipartimento per le Politiche di Coesione e per il Sud. Retrieved from: <https://politichecoesione.governo.it/it/politica-di-coesione/strategie-tematiche-e-territoriali/strategie-territoriali/strategia-nazionale-aree-interne-snai/le-aree-interne-2021-2027/> [Accessed May 20, 2025].

- PCM (2025). OpenCoesione. Presidenza del Consiglio dei Ministri: Dipartimento per le Politiche di Coesione e per il Sud. Retrieved from: <https://opencoesione.gov.it/it/dati/> [Accessed May 20, 2025].
- PCM (2025). Piano Strategico Nazionale delle Aree Interne PSNAI. Technical report, Presidenza del Consiglio dei Ministri.
- Perchinunno, P., d'Ovidio, F. D., and Rotondo, F. (2019). Identification of “Hot Spots” of inner areas in Italy: Scan statistic for urban planning policies. *Social Indicators Research*, 143(3):1299–1317.
- Pike, A., Béal, V., Cauchi-Duval, N., Franklin, R., Kinossian, N., Lang, T., Leibert, T., MacKinnon, D., Rousseau, M., Royer, J., *et al.* (2024). ‘Left behind places’: a geographical etymology. *Regional Studies*, 58(6):1167–1179.
- Rassen, J. A., Shelat, A. A., Myers, J., Glynn, R. J., Rothman, K. J., and Schneeweiss, S. (2012). One-to-many propensity score matching in cohort studies. *Pharmacoepidemiology and drug safety*, 21:69–80.
- Rodríguez-Pose, A. (2018). The revenge of the places that don’t matter (and what to do about it). *Cambridge journal of regions, economy and society*, 11(1):189–209.
- Rodríguez-Rejas, M. J. and Díez-Gutiérrez, E. J. (2021). Territorios en disputa: un estudio de caso en la España vaciada. *Ciudad y Territorio Estudios Territoriales*, 53(208):371–390.
- Romagnoli, L., Di Renzo, P., and Mastronardi, L. (2022). Modelling income drivers in peripheral municipalities: the case of Italian inner areas. *Sustainability*, 14(22):14754.
- Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.
- Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

- Rossi-Doria, M. (1958). *Dieci anni di politica agraria nel Mezzogiorno*. Laterza, Rome, IT.
- Rossitti, M., Dell'Ovo, M., Oppio, A., and Torrieri, F. (2021). The Italian National Strategy for Inner Areas (SNAI): A critical analysis of the indicator grid. *Sustainability*, 13(12):6927.
- Stuart, E. A. and Rubin, D. B. (2008). Best practices in quasi-experimental designs. In Jason, O., editor, *Best practices in quantitative methods*, chapter 11, pages 155–176. SAGE Publications, Inc., New York, NY-US.
- UVAL (2014). Strategia nazionale per le aree interne: Definizione, obiettivi, strumenti e governance. Technical report, Unità di Valutazione degli Investimenti Pubblici.
- Zollet, S. and Qu, M. (2024). Revitalising rural areas through counterurbanisation: Community-oriented policies for the settlement of urban newcomers. *Habitat International*, 145:103022.

Acknowledgments

The authors would like to express their gratitude to Drs. Giorgio Ialenti and Agapito Emanuele Santangelo for their valuable assistance.

Further thanks are extended for the valuable feedback received during the 22nd annual conference of the Italian Association for the History of Political Economy (STOREP), the 46th annual conference of the Italian Association of Regional Sciences (AISRe), the 37th annual conference of the Italian Society of Public Economics (SIEP), and the 38th annual conference of the European Association for Evolutionary Political Economy (EAEPE).

This study was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS - Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP H93C22000650001). The views and opinions expressed are solely those of the authors and do not

necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

Appendix

Table A1: *Resources allocated for Italian Inner Areas (2014–2027)*

Programming	Amount (€ millions)	Description	Law	Coverage Years	Implementing Act	Notes
2014–2020	90	Ensure the effectiveness and sustainability of SNAI	Stability Law 2014 (L. 147/2013)	2015–2026	CIPE Resolution 9/2015	
	90	Strengthening of SNAI	Stability Law 2015 (L. 190/2014)	2015–2017	CIPE Resolution 43/2016	
	10	Interventions for the development of inner areas	Stability Law 2016 (L. 208/2015)	2016–2018	CIPE Resolution 80/2017	
	91.18	Interventions for the development of inner areas	Budget Law 2018 (L. 205/2017)	2019–2021	CIPE Resolution 52/2018	
2021–2027	200	Strengthening and expansion of SNAI and forest fire prevention	Budget Law 2020 (L. 160/2019)	2021–2023	CIPESS Resolutions 41/2022 and 42/2022	40 million have not yet been allocated by CIPESS
	110	Strengthening and expansion of SNAI	Law Decree 104/2020	2020–2021	CIPESS Resolution 41/2022	
	9	Complementary Fund: Municipal Doctorates	Law Decree 34/2020	2021–2023	Ministerial Decree 725/2021	
	300	Complementary Fund: Improving road accessibility and safety in inner areas (74 areas 2014–2020)	Law Decree 59/2021	2021–2026	Ministerial Decree 394/2021	
	50	Increased resources of the Complementary Fund: Roads in Inner Areas (43 areas 2021–2027)	Budget Law 2022 (L. 234/2021)	2023–2024	Interministerial Decree 170/2023	
	500	Strengthening of community social services and infrastructure	NRRP: European Structural and Investment Funds (Mission 5, Component 3)	2021–2026		Initially 750 million were planned
	100	Local proximity healthcare services	NRRP: European Structural and Investment Funds (Mission 5, Component 3)	2021–2026		
Support Fund for marginal municipalities	210	Support for economic, craft, and commercial activities in inner municipalities	L. 160/2019, D.L. 34/2020	2021–2023	Prime Minister's Decree 24/09/2021	
	180	Support for disadvantaged municipalities	D.L. 34/2020, L. 178/2020	2021–2023	Prime Minister's Decree 30/09/2021	Not exclusively referable to inner areas
	136	To counter the phenomenon of deindustrialization	L. 178/2020	2021–2023	Prime Minister's Decree 30/11/2021	Not exclusively referable to inner areas

Notes: CIPE stands for Interministerial Committee for Economic Planning (*Comitato interministeriale per la programmazione economica*); CIPESS stands for Interministerial Committee for Economic Planning and Sustainable Development (*Comitato interministeriale per la programmazione economica e lo sviluppo sostenibile*); NRRP stands for National Recovery and Resilience Plan (*Piano Nazionale di Ripresa e Resilienza*).

Sources: Authors' personal elaboration based on [CdD \(2023\)](#) and [PCM \(2025\)](#).

Figure A1: *Municipality classification, comparison between 2019 (SNAI 2021–2027) and 2025*

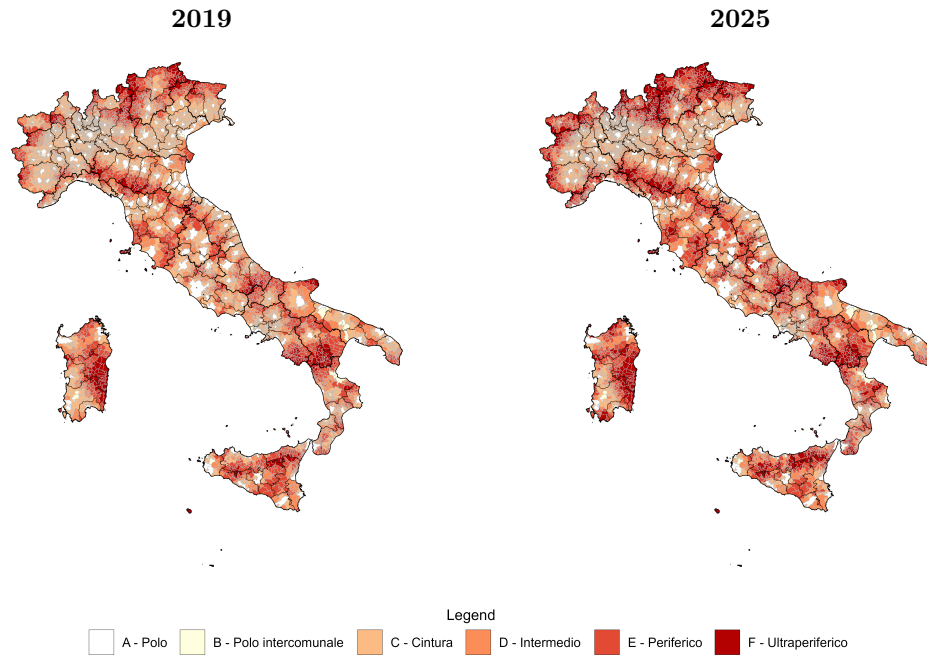
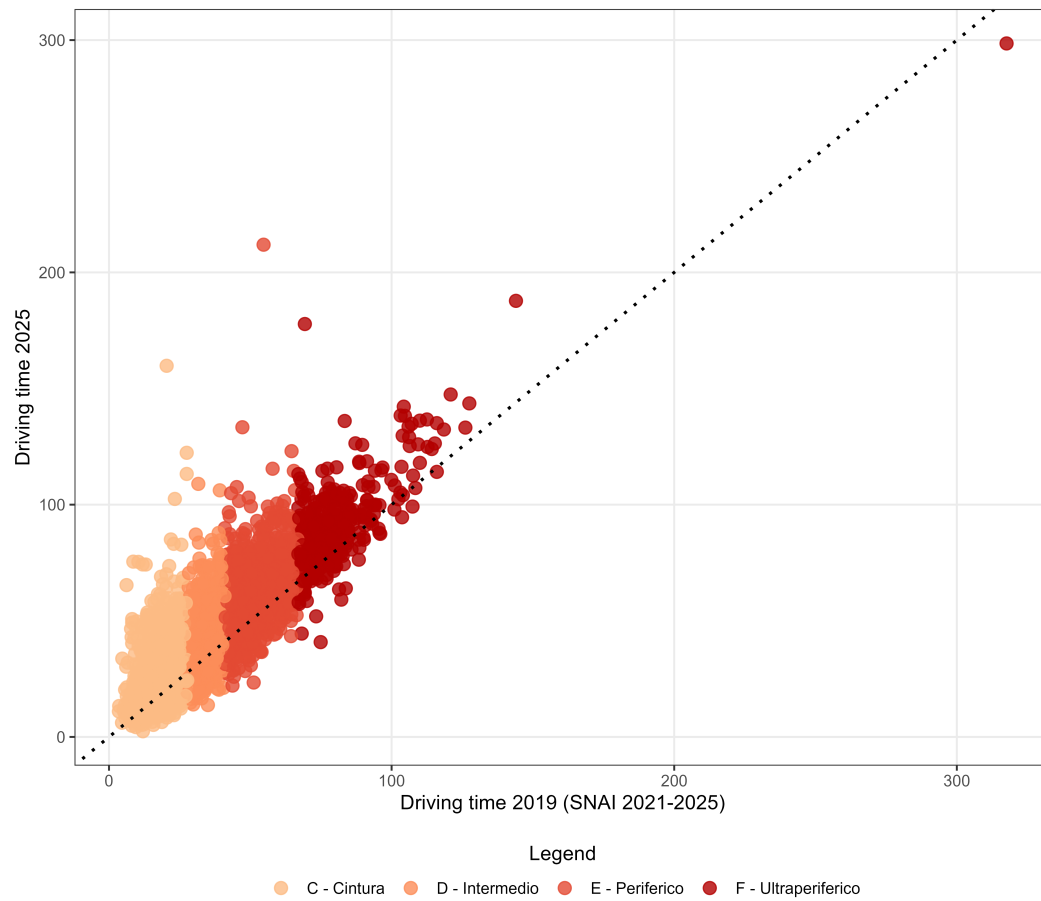


Figure A2: *Municipality driving time, comparison between 2019 (SNAI 2021–2027) and 2025*



Notes: Municipality colours refers to the SNAI 2021–2027 classification.

Figure A3: *Share of municipalities classified as Inner Areas by region, comparison between 2019 (SNAI 2021–2027) and 2025*

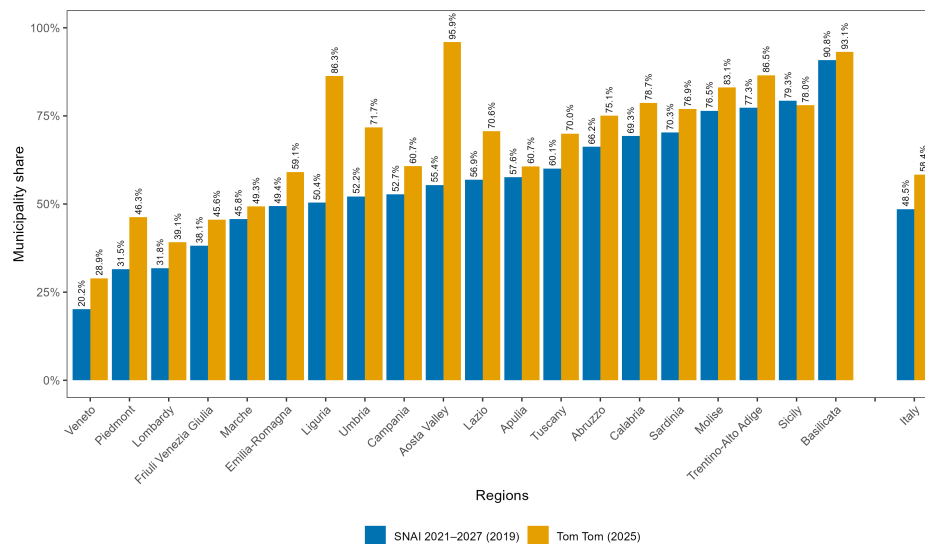


Figure A4: *Share of surface classified as Inner Areas by region, comparison between 2019 (SNAI 2021–2027) and 2025*

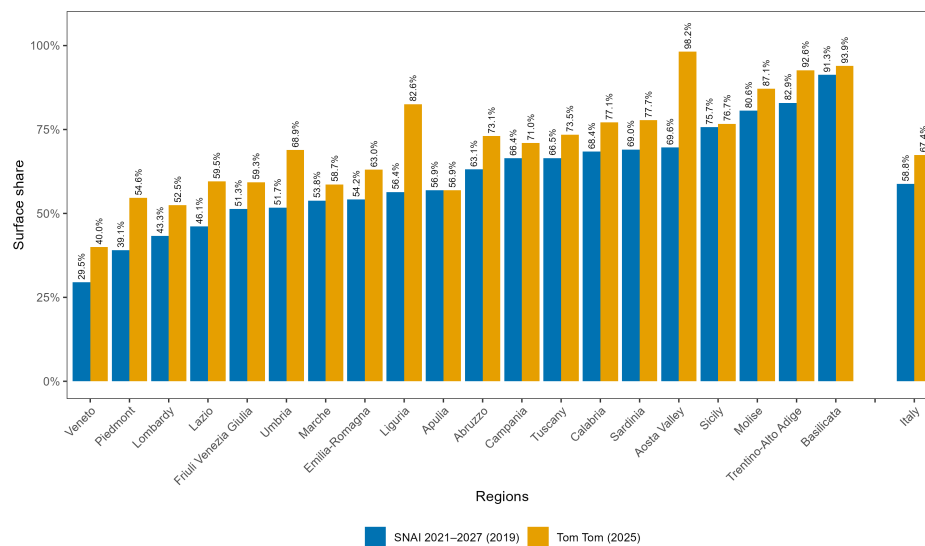


Figure A5: *Share of population classified in Inner Areas by region, comparison between 2019 (SNAI 2021–2027) and 2025*

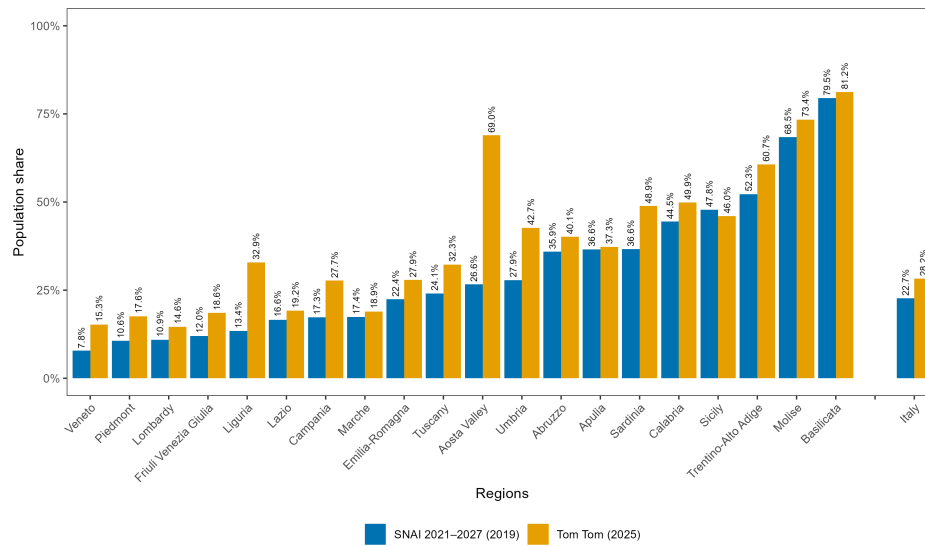
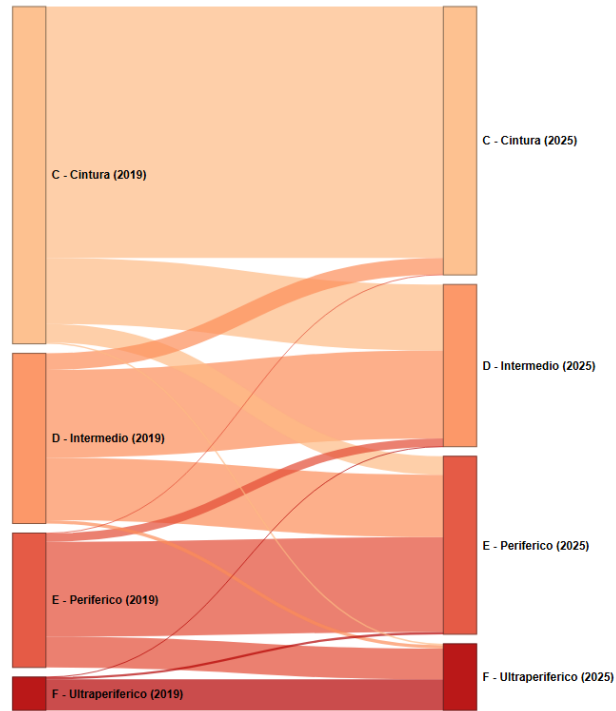
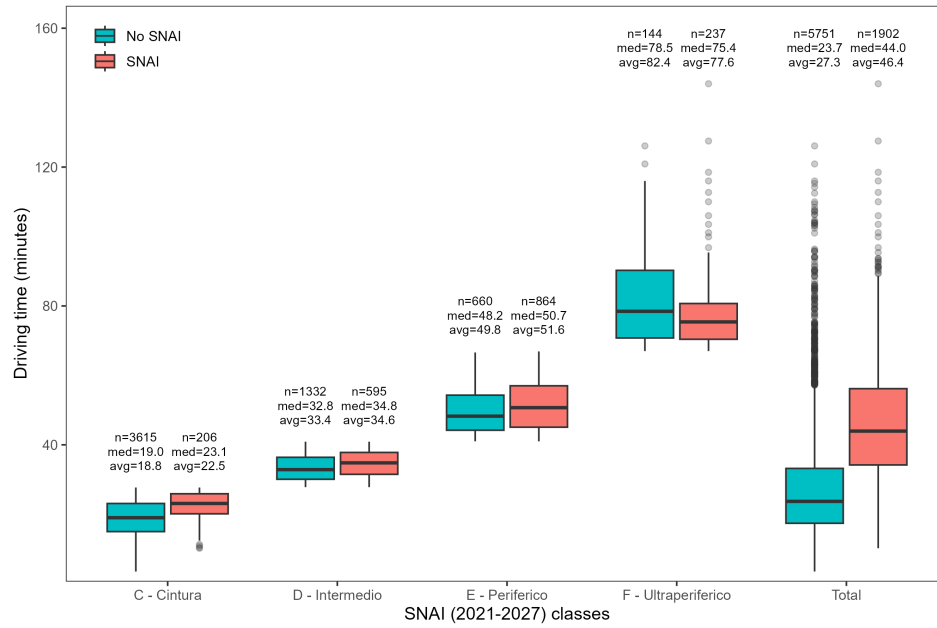


Figure A6: *Sankey network for changes in area classification in 2025 compared to the SNAI 2021–2027 framework*



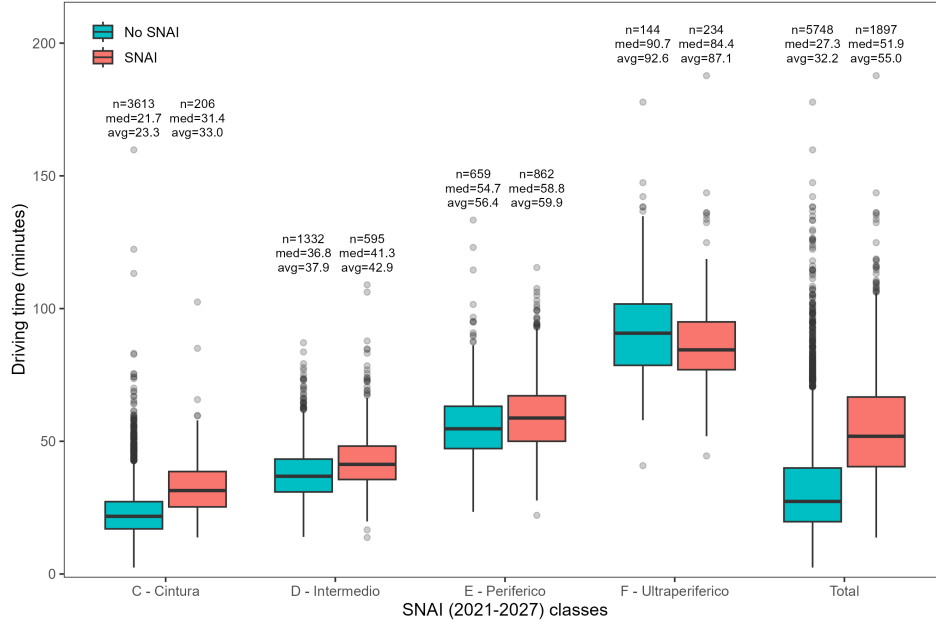
Notes: Nodes on the left represent municipalities divided as belt, intermediate, peripheral, and ultra peripheral as defined by the classification SNAI 2021–2027 which relies on 2019 data. Nodes on the right, instead, represent the composition of municipalities as resulted from the analysis made with Tom Tom data for 2025.

Figure A7: *Box plot for driving time calculated in 2019 for SNAI and no-SNAI areas clustered by SNAI 2021–2027 framework*



Notes: Municipalities outliers with duration time exceeding 200 minutes are not showed in the graph.

Figure A8: *Box plot for driving time calculated in 2025 for SNAI and no-SNAI areas clustered by SNAI 2021–2027 framework*



Notes: Municipalities outliers with duration time exceeding 200 minutes are not showed in the graph.

Table A2: *Descriptive statistics*

Variable	Description	Mean	SD	Min	Q1	Median	Q3	Max
Y_2019	Driving time (2019, SNAI 2021–2027)	31.870	17.066	3.500	19.300	27.700	40.700	126.100
Y_2025	Driving time (2025)	37.683	20.896	2.438	21.931	32.621	48.820	211.920
sur	Surface	35.822	43.328	0.112	11.360	21.882	42.552	592.949
alt	Altitude	470.113	456.770	0.364	137.301	323.027	649.833	2,776.956
pop	Total population	4,881.575	7,351.934	30.000	968.000	2,304.000	5,656.000	87,039.000
pop_fem_per	Share of female population	50.348	1.670	30.952	49.667	50.523	51.307	57.692
pop_for_per	Share of foreign population	6.524	4.194	0.000	3.284	5.857	8.902	35.802
net_mig	Total net migration	-1.775	13.831	-252.033	-7.711	-1.154	4.897	70.175
pop_14_per	Share of population 0–14	12.091	2.664	0.000	10.478	12.260	13.921	23.026
pop_65_per	Share of population over 65	25.081	5.467	8.419	21.449	24.515	27.995	64.384
bir_rat	Birth rate	6.310	2.751	0.000	4.785	6.398	7.889	31.250
tax_inc	Taxable income	18,269.028	3,770.906	6,774.394	15,357.823	18,440.245	20,911.934	48,507.438
emp_rat	Employment rate	45.197	7.564	21.739	39.295	46.075	50.998	70.331
une_rat	Unemployment rate	11.951	6.236	0.893	7.309	9.812	16.045	39.423
ina_rat	Inactivity rate	48.936	6.097	28.464	44.529	48.463	52.977	77.174
ent_rat	Entrepreneurship rate	59.084	20.624	6.231	46.047	56.807	68.957	271.739
ist_bur	Bureaucratic capacity	99.039	5.321	65.075	97.341	99.947	102.003	119.324
ist_pol	Quality of local politicians	107.111	9.529	83.656	101.168	106.504	113.851	138.724
ist_eco	Fiscal & economic performance	103.399	3.909	80.843	101.384	103.814	105.864	120.373
tou_ove_res	Overnight stays, residents	4,867.794	20,827.920	0.000	0.000	0.000	1,931.000	696,959.000
tou_ove_for	Overnight stays, foreigners	4,190.287	24,318.058	0.000	0.000	0.000	675.750	679,398.000

Notes: SD refers to the standard deviation, while Q1 and Q3 indicate the first (25th percentile) and third (75th percentile) quartiles, respectively.

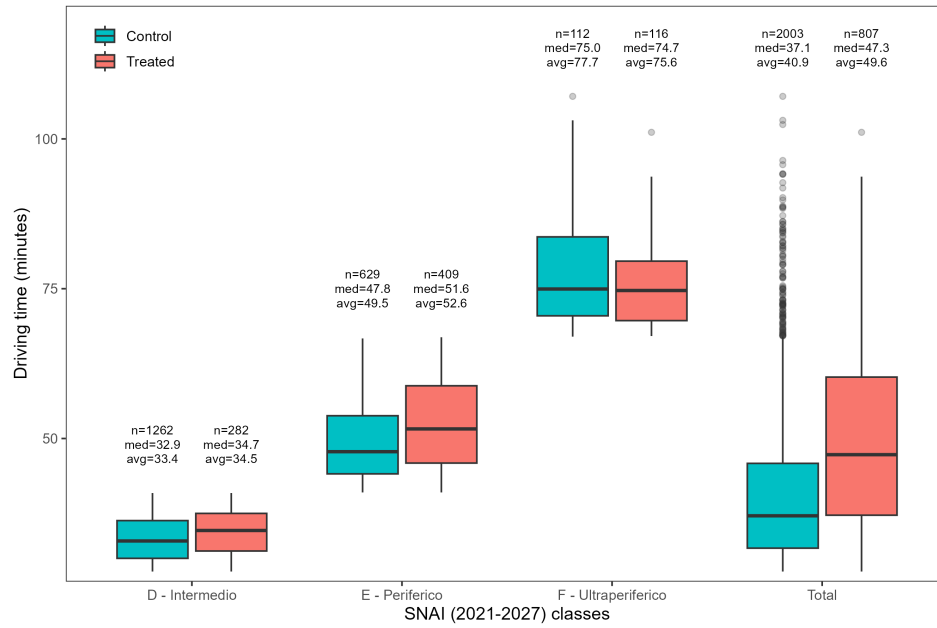
Table A3: *Descriptive statistics (before PSM)*

Variable			<i>All units</i>					<i>Control</i>					<i>Treated</i>		
	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max
Y_2019	44.055	15.043	27.800	39.700	126.100	44.055	15.043	27.800	39.700	126.100	44.055	15.043	27.800	39.700	126.100
Y_2025	50.315	19.807	13.726	45.936	211.920	50.315	19.807	13.726	45.936	211.920	50.315	19.807	13.726	45.936	211.920
treated	0.283	0.450	0.000	0.000	1.000										
sur	43.008	49.876	0.112	26.681	592.949	41.580	50.454	0.112	25.034	592.949	46.631	48.219	1.707	31.480	372.742
alt	594.828	488.636	0.638	465.622	2,637.985	554.556	503.262	0.638	395.530	2,637.985	696.981	433.207	28.462	615.356	2,515.294
pop	3,906.336	6,513.669	30.000	1,684.000	72,187.000	4,556.685	7,363.326	32.000	1,932.000	72,187.000	2,256.691	2,958.284	30.000	1,265.000	30,247.000
pop_fem_per	50.277	1.877	30.952	50.490	56.173	50.304	1.816	30.952	50.492	56.173	50.207	2.025	39.098	50.484	55.752
pop_for_per	6.003	4.421	0.000	4.963	35.802	6.157	4.380	0.000	5.162	35.802	5.612	4.504	0.000	4.366	30.243
net_mig	-2.812	15.303	-252.033	-2.561	69.841	-2.089	15.113	-252.033	-2.017	68.182	-4.645	15.636	-69.090	-4.193	69.841
pop_14_per	11.550	2.725	0.943	11.611	23.026	11.909	2.644	0.943	11.935	23.026	10.639	2.719	1.923	10.673	16.971
pop_65_per	25.966	5.518	10.803	25.541	64.384	25.214	5.243	10.803	24.767	64.384	27.871	5.738	14.607	27.315	50.485
bir_rat	6.185	2.947	0.000	6.191	22.556	6.303	2.816	0.000	6.345	22.556	5.887	3.239	0.000	5.820	22.222
tax_inc	16,844.778	3,561.572	6,774.394	16,727.764	48,484.686	17,271.932	3,545.246	7,489.370	17,253.587	37,616.396	15,761.279	3,369.899	6,774.394	15,316.840	48,484.686
emp_rat	42.629	7.903	22.872	41.961	70.331	43.376	8.035	23.392	43.094	70.331	40.735	7.225	22.872	40.084	70.205
une_rat	13.570	7.009	0.893	12.721	39.423	13.413	7.190	0.893	12.550	39.423	13.967	6.515	0.971	13.023	36.742
ent_rat	58.002	23.122	9.346	54.470	271.739	59.288	23.894	9.346	55.539	271.739	54.742	20.696	9.780	51.709	189.074
ist_bur	98.989	5.816	68.727	99.939	119.324	99.013	5.666	68.727	99.945	119.324	98.927	6.183	73.468	99.916	115.114
ist_pol	106.267	9.806	83.656	105.085	135.009	106.822	9.749	83.656	105.897	135.009	104.859	9.816	84.136	104.212	132.483
ist_eco	102.890	4.270	80.843	103.238	116.891	103.006	4.303	80.843	103.438	116.891	102.595	4.173	86.342	102.882	113.519
tou_ove_res	5,288.758	17,650.244	0.000	0.000	239,420.000	6,470.385	19,876.166	0.000	0.000	239,420.000	2,291.497	9,345.423	0.000	0.000	163,620.000
tou_ove_for	5,229.995	26,075.574	0.000	0.000	635,531.000	6,618.026	30,247.917	0.000	0.000	635,531.000	1,709.177	8,181.304	0.000	0.000	103,646.000

Table A4: *Descriptive statistics (post PSM)*

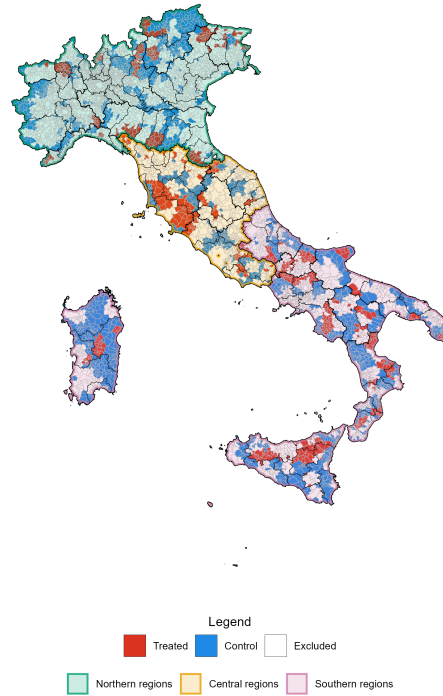
Variable			<i>All units</i>					<i>Control</i>					<i>Treated</i>		
	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max
Y_2019	43.412	13.929	27.800	39.400	107.100	43.412	13.929	27.800	39.400	107.100	43.412	13.929	27.800	39.400	107.100
Y_2025	49.578	18.471	13.726	45.542	211.920	49.578	18.471	13.726	45.542	211.920	49.578	18.471	13.726	45.542	211.920
treated	0.287	0.453	0.000	0.000	1.000										
sur	42.311	49.230	0.112	26.387	592.949	40.570	49.537	0.112	24.528	592.949	46.631	48.219	1.707	31.480	372.742
alt	598.839	487.248	0.705	469.941	2,637.985	559.299	502.104	0.705	403.385	2,637.985	696.981	433.207	28.462	615.356	2,515.294
pop	3,505.287	5,316.617	30.000	1,662.000	69,999.000	4,008.340	5,937.643	32.000	1,882.000	69,999.000	2,256.691	2,958.284	30.000	1,265.000	30,247.000
pop_fem_per	50.266	1.885	30.952	50.478	56.173	50.290	1.826	30.952	50.472	56.173	50.207	2.025	39.098	50.484	55.752
pop_for_per	5.983	4.415	0.000	4.951	35.802	6.132	4.372	0.000	5.153	35.802	5.612	4.504	0.000	4.366	30.243
net_mig	-2.865	15.401	-252.033	-2.677	69.841	-2.147	15.250	-252.033	-2.043	68.182	-4.645	15.636	-69.090	-4.193	69.841
pop_14_per	11.523	2.720	0.943	11.579	23.026	11.879	2.638	0.943	11.876	23.026	10.639	2.719	1.923	10.673	16.971
pop_65_per	26.030	5.509	10.803	25.622	64.384	25.288	5.236	10.803	24.849	64.384	27.871	5.738	14.607	27.315	50.485
bir_rat	6.166	2.956	0.000	6.159	22.556	6.279	2.827	0.000	6.309	22.556	5.887	3.239	0.000	5.820	22.222
tax_inc	16,807.680	3,549.347	6,774.394	16,668.144	48,484.686	17,229.270	3,533.390	7,489.370	17,175.209	37,616.396	15,761.279	3,369.899	6,774.394	15,316.840	48,484.686
emp_rat	42.606	7.912	22.872	41.917	70.331	43.360	8.052	23.392	43.070	70.331	40.735	7.225	22.872	40.084	70.205
une_rat	13.536	6.990	0.893	12.642	39.423	13.363	7.167	0.893	12.474	39.423	13.967	6.515	0.971	13.023	36.742
ent_rat	57.741	22.931	9.346	54.271	271.739	58.950	23.671	9.346	55.046	271.739	54.742	20.696	9.780	51.709	189.074
ist_bur	98.981	5.849	68.727	99.956	119.324	99.002	5.711	68.727	99.978	119.324	98.927	6.183	73.468	99.916	115.114
ist_pol	106.170	9.794	83.656	105.085	135.009	106.698	9.738	83.656	105.711	135.009	104.859	9.816	84.136	104.212	132.483
ist_eco	102.888	4.288	80.843	103.254	116.891	103.007	4.329	80.843	103.459	116.891	102.595	4.173	86.342	102.882	113.519
tou_ove_res	4,265.736	13,627.204	0.000	0.000	170,900.000	5,061.148	14,939.556	0.000	0.000	170,900.000	2,291.497	9,345.423	0.000	0.000	163,620.000
tou_ove_for	3,764.301	14,866.979	0.000	0.000	207,925.000	4,592.302	16,756.688	0.000	0.000	207,925.000	1,709.177	8,181.304	0.000	0.000	103,646.000

Figure A9: *Box plot for driving time calculated in 2025 for SNAI and no-SNAI areas clustered by SNAI 2021–2027 framework after PSM*



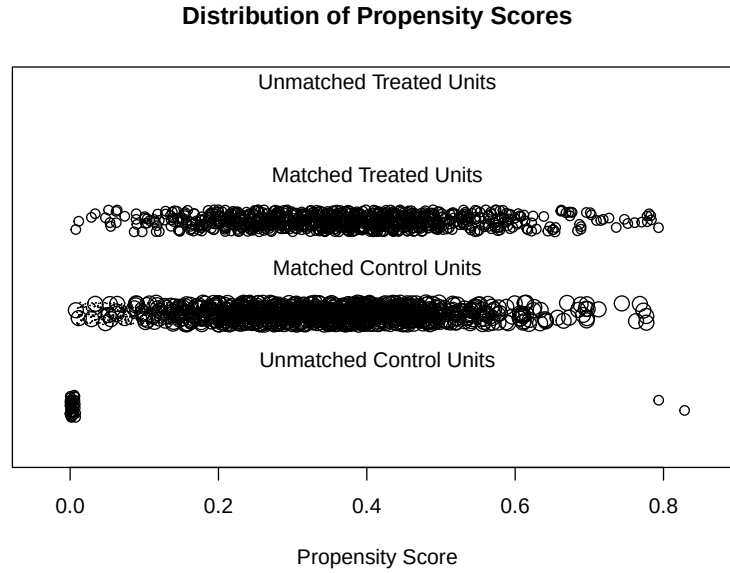
Notes: Municipalities outliers with duration time exceeding 200 minutes are not showed in the graph.

Figure A10: *Identification of treated units for SNAI 2021–2027 after PSM*



Notes: 807 Treated, 2,003 Untreated, and 5,086 Excluded.

Figure A11: *Distribution of the PSM and common support*



Group	Control	Treated
All	2,047	807
Matched (ESS)	808	807
Matched	2,003	807
Unmatched	0	0
Discarded	44	0

The Effective Sample Size (ESS) represents the weighted number of observations retained in the matched sample. Unmatched units are observations that were not paired during the matching procedure because no suitable counterpart was found within the specified matching criteria, in our case the caliper restriction. Discarded units are observations excluded due to the lack of common support, which refers to the overlap in propensity score distributions between treated and control groups. These observations are removed prior to matching because their propensity scores fall outside the overlapping region, preventing meaningful comparisons between treated and control units.

Figure A12: *Absolute standardized mean difference for covariates*

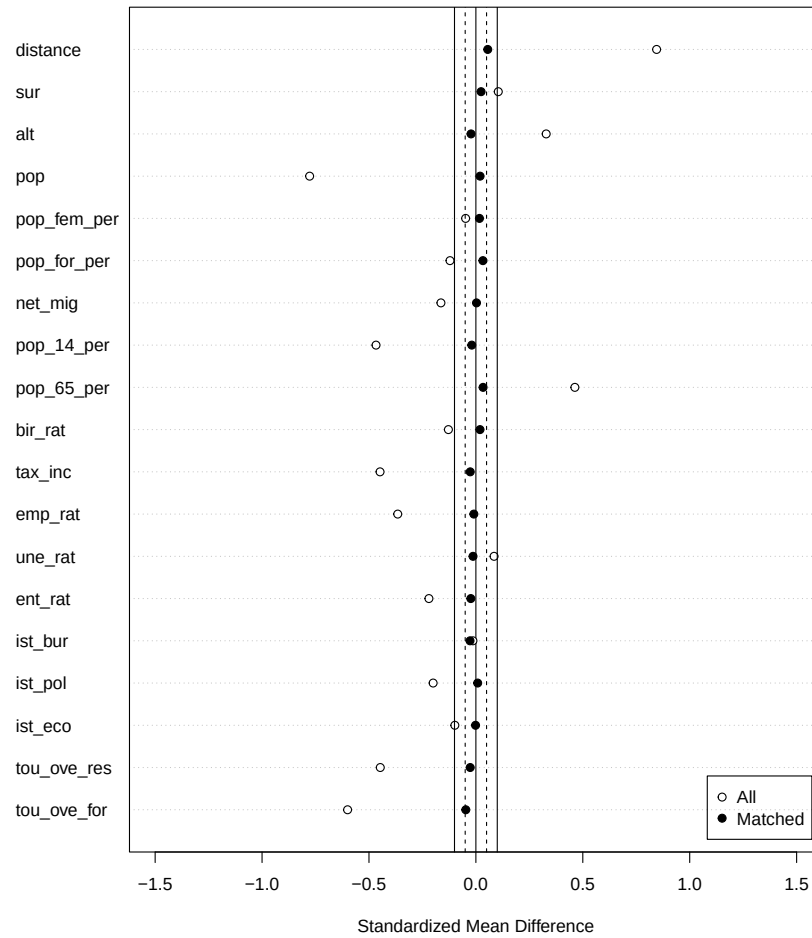


Figure A13: *Balancing graph before and after the PSM*

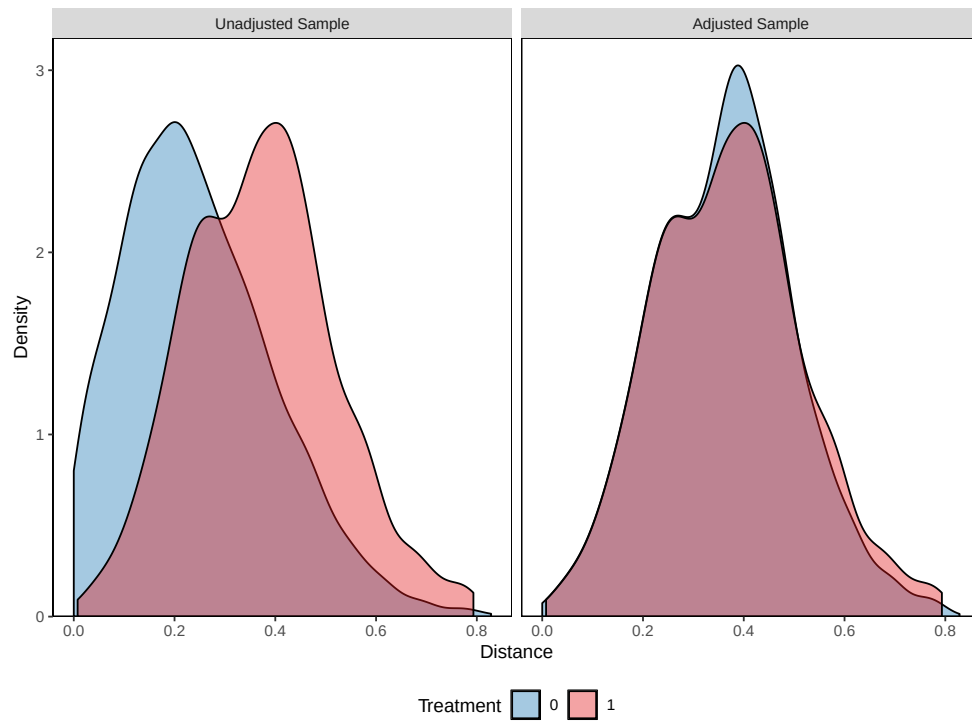
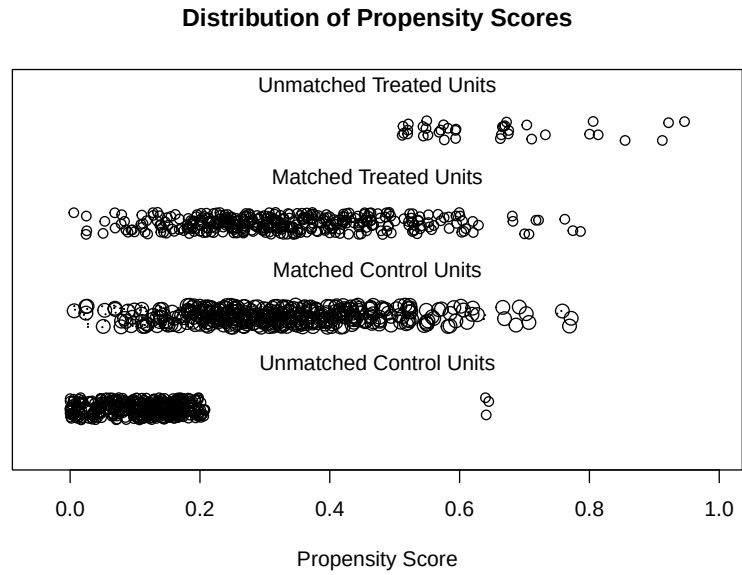


Figure A14: *Distribution of the PSM and common support (North-Center regions)*



Group	Control	Treated
All	1,159	409
Matched (ESS)	373	372
Matched	772	372
Unmatched	367	37
Discarded	20	0

Figure A15: *Absolute standardized mean difference for covariates (North-Center regions)*

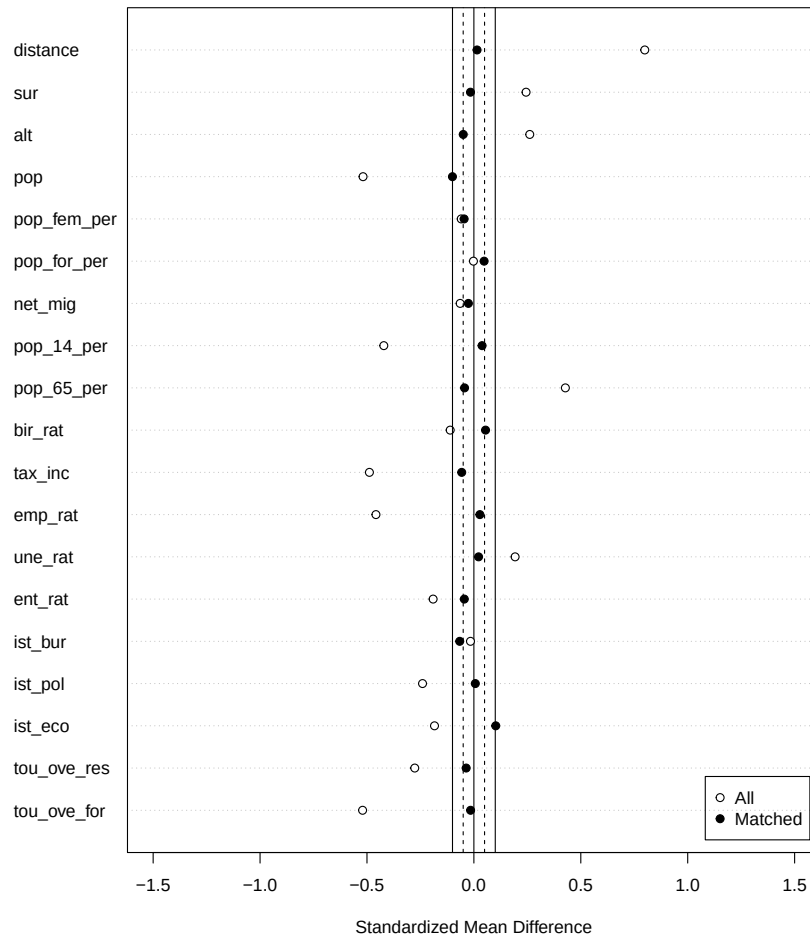


Figure A16: *Balancing graph before and after the PSM (North-Center regions)*

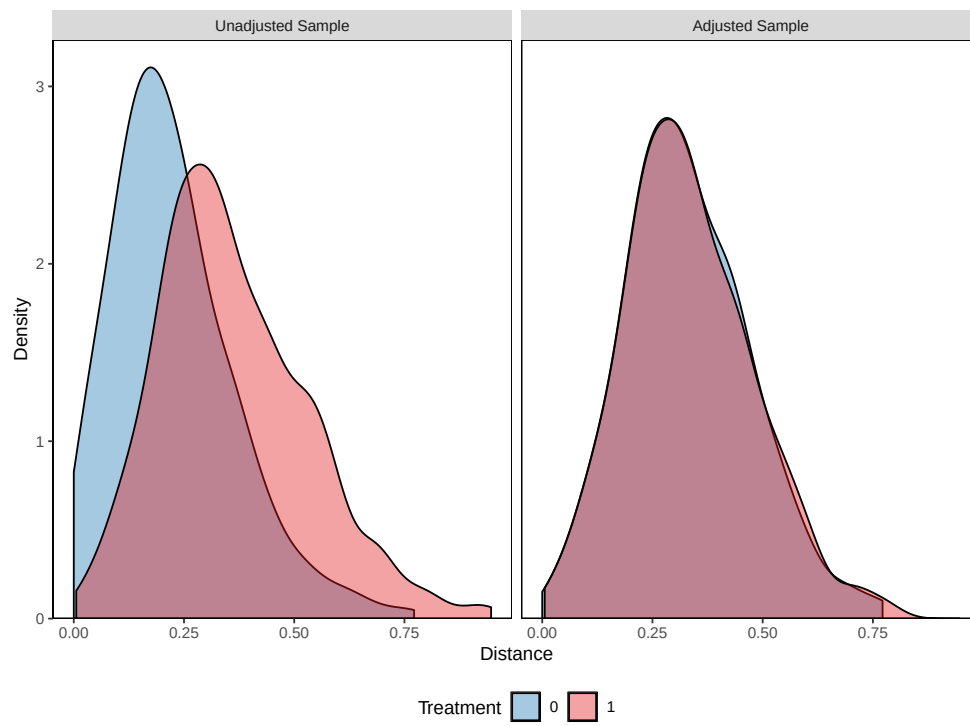
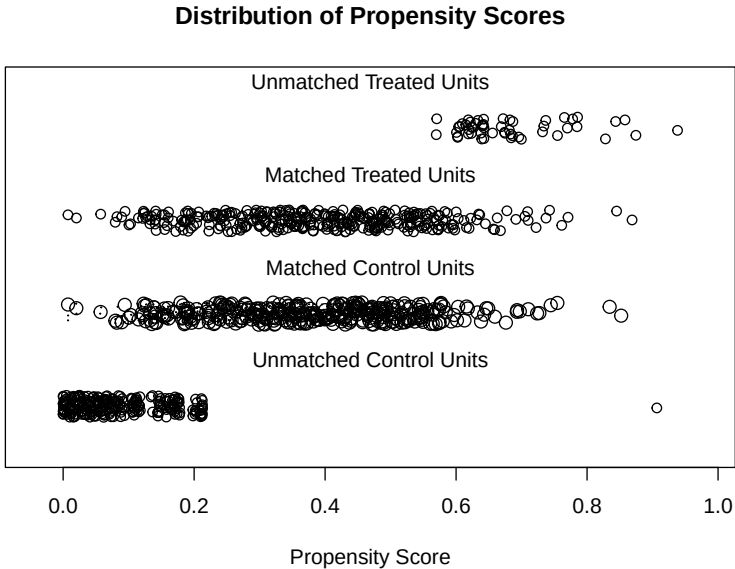


Figure A17: *Distribution of the PSM and common support (South regions)*



Group	Control	Treated
All	888	398
Matched (ESS)	346	345
Matched	640	345
Unmatched	225	53
Discarded	23	0

Figure A18: *Absolute standardized mean difference for covariates (South regions)*

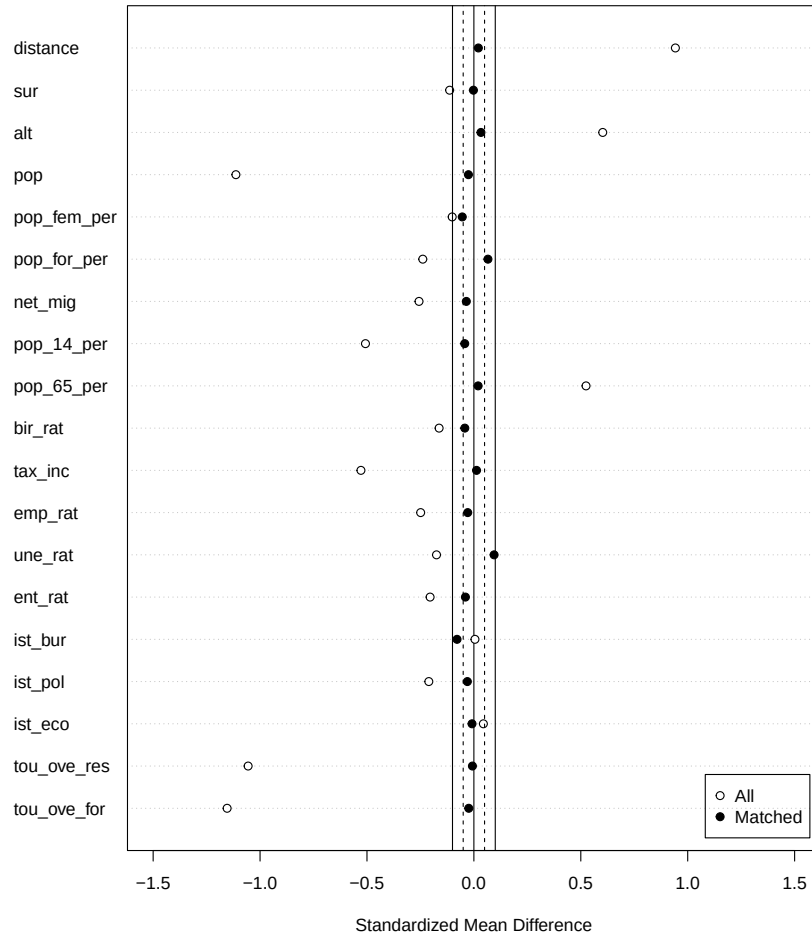


Figure A19: *Balancing graph before and after the PSM (South regions)*

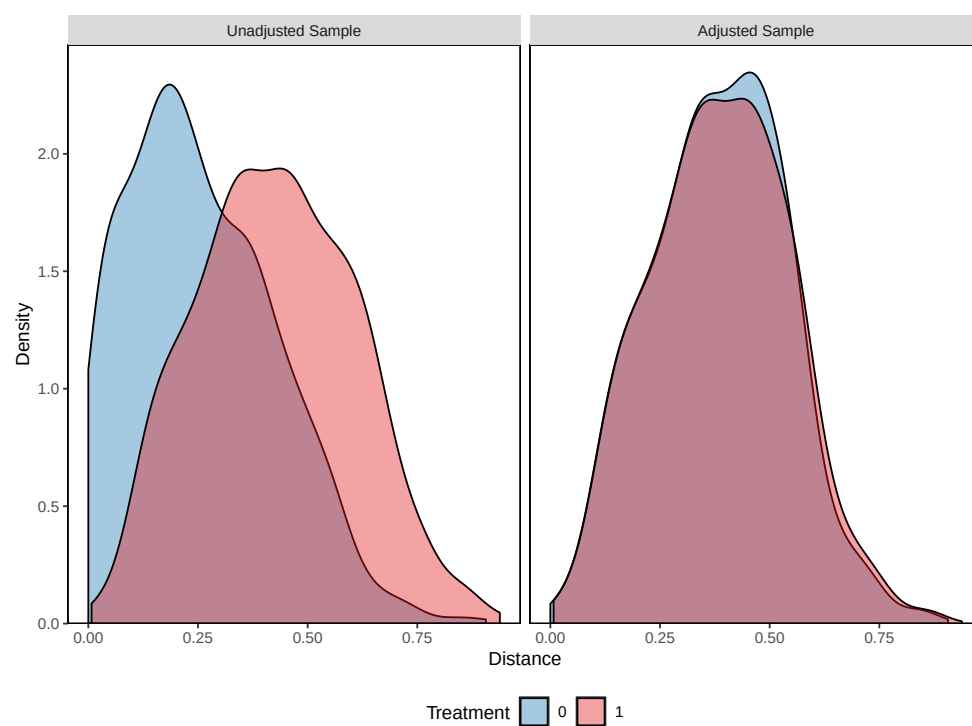


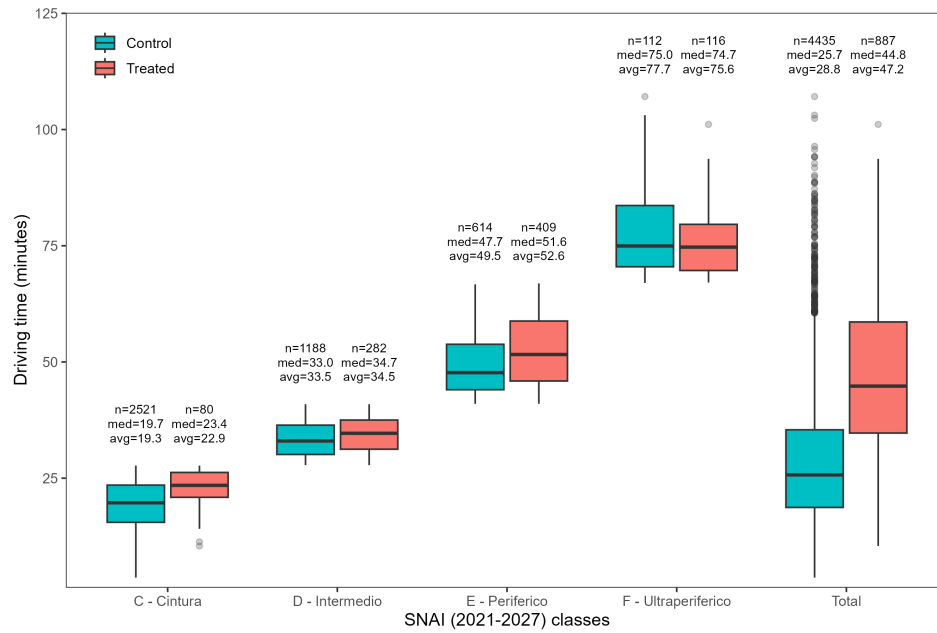
Table A5: *Descriptive statistics (with belt municipalities, before PSM)*

Variable			<i>All units</i>					<i>Control</i>					<i>Treated</i>		
	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max	Mean	SD	Min	Median	Max
Y_2019	30.306	16.564	3.500	26.100	126.100	30.306	16.564	3.500	26.100	126.100	30.306	16.564	3.500	26.100	126.100
Y_2025	35.580	20.267	2.438	30.060	211.920	35.580	20.267	2.438	30.060	211.920	35.580	20.267	2.438	30.060	211.920
treated	0.139	0.346	0.000	0.000	1.000										
sur	32.254	40.514	0.112	19.423	592.949	30.190	39.000	0.112	18.114	592.949	45.057	46.907	1.707	30.884	372.742
alt	415.689	423.229	0.552	281.138	2,637.985	372.400	406.782	0.552	241.907	2,637.985	684.156	424.585	28.462	596.398	2,515.294
pop	5,263.846	7,655.377	30.000	2,549.000	87,039.000	5,747.474	8,060.193	32.000	2,879.000	87,039.000	2,264.481	2,952.907	30.000	1,265.000	30,247.000
pop_fem_per	50.394	1.574	30.952	50.547	56.364	50.420	1.494	30.952	50.555	56.364	50.231	1.996	39.098	50.497	55.752
pop_for_per	6.711	4.214	0.000	6.044	35.802	6.881	4.154	0.000	6.213	35.802	5.656	4.430	0.000	4.437	30.243
net_mig	-1.391	13.544	-252.033	-0.861	70.175	-0.942	13.083	-252.033	-0.376	70.175	-4.174	15.840	-69.090	-3.847	69.841
pop_14_per	12.391	2.547	0.926	12.557	23.026	12.669	2.413	0.926	12.799	23.026	10.664	2.674	1.923	10.763	16.971
pop_65_per	24.485	5.099	9.019	23.997	64.384	23.945	4.794	9.019	23.567	64.384	27.833	5.631	14.607	27.430	50.485
bir_rat	6.440	2.666	0.000	6.544	31.250	6.534	2.554	0.000	6.640	31.250	5.858	3.220	0.000	5.812	22.222
tax_inc	18,563.473	3,824.705	6,774.394	18,831.251	48,507.438	18,979.032	3,716.582	7,489.370	19,274.923	48,507.438	15,986.253	3,461.910	6,774.394	15,540.173	48,484.686
emp_rat	45.629	7.630	22.872	46.777	70.331	46.369	7.447	23.392	47.727	70.331	41.034	7.135	22.872	40.587	70.205
une_rat	11.931	6.279	0.893	9.640	39.423	11.639	6.213	0.893	9.292	39.423	13.738	6.384	0.971	12.682	36.742
ent_rat	59.017	19.779	9.346	57.075	271.739	59.700	19.602	9.346	57.742	271.739	54.780	20.351	9.780	51.813	189.074
ist_bur	98.990	5.193	68.679	99.898	119.324	98.986	5.026	68.679	99.880	119.324	99.011	6.131	73.217	100.034	115.114
ist_pol	107.489	9.501	83.656	107.153	135.009	107.896	9.370	83.656	107.267	135.009	104.968	9.921	84.136	104.467	132.483
ist_eco	103.392	3.836	80.843	103.795	120.373	103.508	3.751	80.843	103.917	120.373	102.671	4.255	86.342	103.037	119.581
tou_ove_res	4,997.302	21,677.460	0.000	0.000	696,959.000	5,444.083	23,045.483	0.000	0.000	696,959.000	2,226.458	9,039.864	0.000	0.000	163,620.000
tou_ove_for	4,484.615	26,103.290	0.000	0.000	679,398.000	4,931.861	27,917.584	0.000	0.000	679,398.000	1,710.887	8,049.454	0.000	0.000	103,646.000

Table A6: *Descriptive statistics (with belt municipalities, post PSM)*

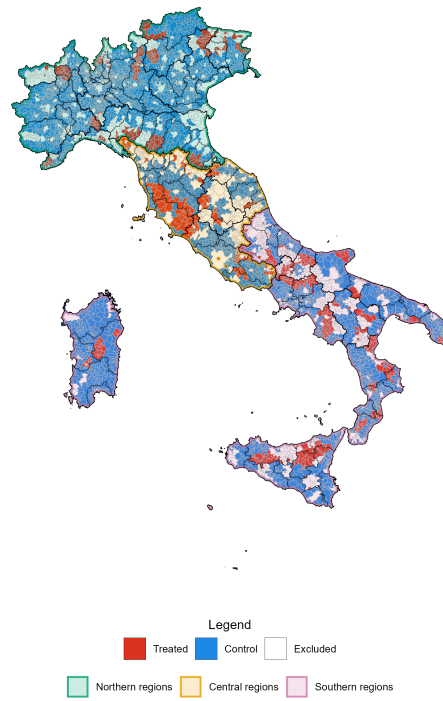
Variable	Mean	SD	<i>All units</i> Min	Median	Max	Mean	SD	<i>Control</i> Min	Median	Max	Mean	SD	<i>Treated</i> Min	Median	Max
Y_2019	31.826	16.124	3.600	28.100	107.100	31.826	16.124	3.600	28.100	107.100	31.826	16.124	3.600	28.100	107.100
Y_2025	37.552	19.697	4.830	33.000	211.920	37.552	19.697	4.830	33.000	211.920	37.552	19.697	4.830	33.000	211.920
treated	0.167	0.373	0.000	0.000	1.000										
sur	33.265	41.075	0.112	20.445	592.949	30.907	39.390	0.112	18.732	592.949	45.057	46.907	1.707	30.884	372.742
alt	465.532	438.500	0.552	334.232	2,637.985	421.807	428.079	0.552	286.845	2,637.985	684.156	424.585	28.462	596.398	2,515.294
pop	3,442.530	4,221.514	30.000	2,010.000	55,324.000	3,678.140	4,394.396	32.000	2,190.000	55,324.000	2,264.481	2,952.907	30.000	1,265.000	30,247.000
pop_fem_per	50.341	1.667	30.952	50.515	56.364	50.363	1.592	30.952	50.518	56.364	50.231	1.996	39.098	50.497	55.752
pop_for_per	6.509	4.278	0.000	5.703	35.802	6.679	4.227	0.000	5.916	35.802	5.656	4.430	0.000	4.437	30.243
net_mig	-2.025	14.412	-252.033	-1.800	70.175	-1.596	14.072	-252.033	-1.423	70.175	-4.174	15.840	-69.090	-3.847	69.841
pop_14_per	11.975	2.480	0.926	12.068	23.026	12.238	2.353	0.926	12.320	23.026	10.664	2.674	1.923	10.763	16.971
pop_65_per	25.273	4.972	10.012	24.897	64.384	24.761	4.665	10.012	24.462	64.384	27.833	5.631	14.607	27.430	50.485
bir_rat	6.256	2.797	0.000	6.270	31.250	6.336	2.698	0.000	6.360	31.250	5.858	3.220	0.000	5.812	22.222
tax_inc	17,838.326	3,437.716	6,774.394	18,242.613	48,484.686	18,208.741	3,311.159	7,489.370	18,630.146	31,114.240	15,986.253	3,461.910	6,774.394	15,540.173	48,484.686
emp_rat	44.599	7.413	22.872	45.620	70.331	45.312	7.261	23.392	46.459	70.331	41.034	7.135	22.872	40.587	70.205
une_rat	12.302	6.354	0.893	10.278	39.423	12.015	6.310	0.893	9.864	39.423	13.738	6.384	0.971	12.682	36.742
ent_rat	57.322	19.787	9.346	54.991	271.739	57.830	19.635	9.346	55.502	271.739	54.780	20.351	9.780	51.813	189.074
ist_bur	98.882	5.514	68.679	99.860	119.324	98.856	5.382	68.679	99.839	119.324	99.011	6.131	73.217	100.034	115.114
ist_pol	106.563	9.580	83.656	105.897	135.009	106.882	9.479	83.656	105.897	135.009	104.968	9.921	84.136	104.467	132.483
ist_eco	103.256	3.985	80.843	103.667	120.373	103.373	3.918	80.843	103.823	120.373	102.671	4.255	86.342	103.037	119.581
tou_ove_res	2,883.174	10,342.513	0.000	0.000	170,900.000	3,014.517	10,579.853	0.000	0.000	170,900.000	2,226.458	9,039.864	0.000	0.000	163,620.000
tou_ove_for	2,486.672	12,057.342	0.000	0.000	240,327.000	2,641.828	12,703.166	0.000	0.000	240,327.000	1,710.887	8,049.454	0.000	0.000	103,646.000

Figure A20: *Box plot for driving time calculated in 2025 for SNAI and no-SNAI areas clustered by SNAI 2021–2027 framework after PSM (model with belt municipalities)*



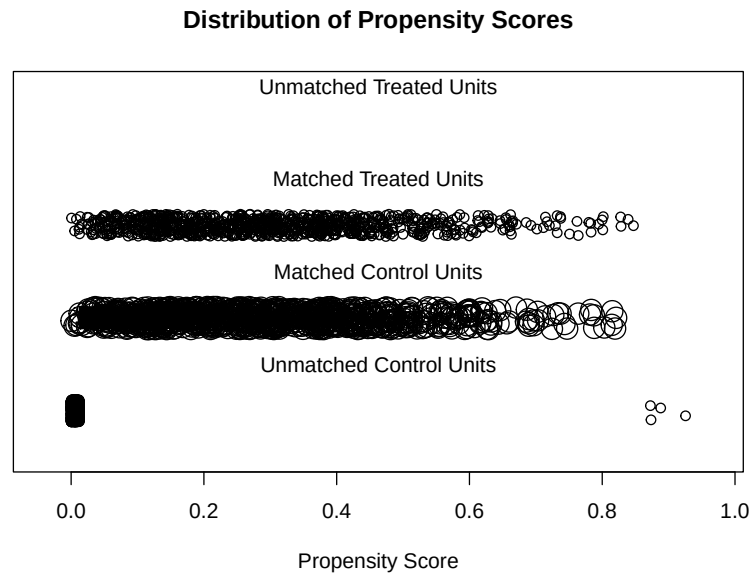
Notes: Municipalities outliers with duration time exceeding 200 minutes are not showed in the graph.

Figure A21: *Identification of treated units for SNAI 2021–2027 after PSM (model with belt municipalities)*



Notes: 887 Treated, 4,435 Untreated, and 2,574 Excluded.

Figure A22: *Distribution of the PSM and common support (model with belt municipalities)*



Group	Control	Treated
All	5,501	887
Matched (ESS)	888	887
Matched	4,435	887
Unmatched	924	0
Discarded	142	0

Figure A23: *Absolute standardized mean difference for covariates (model with belt municipalities)*

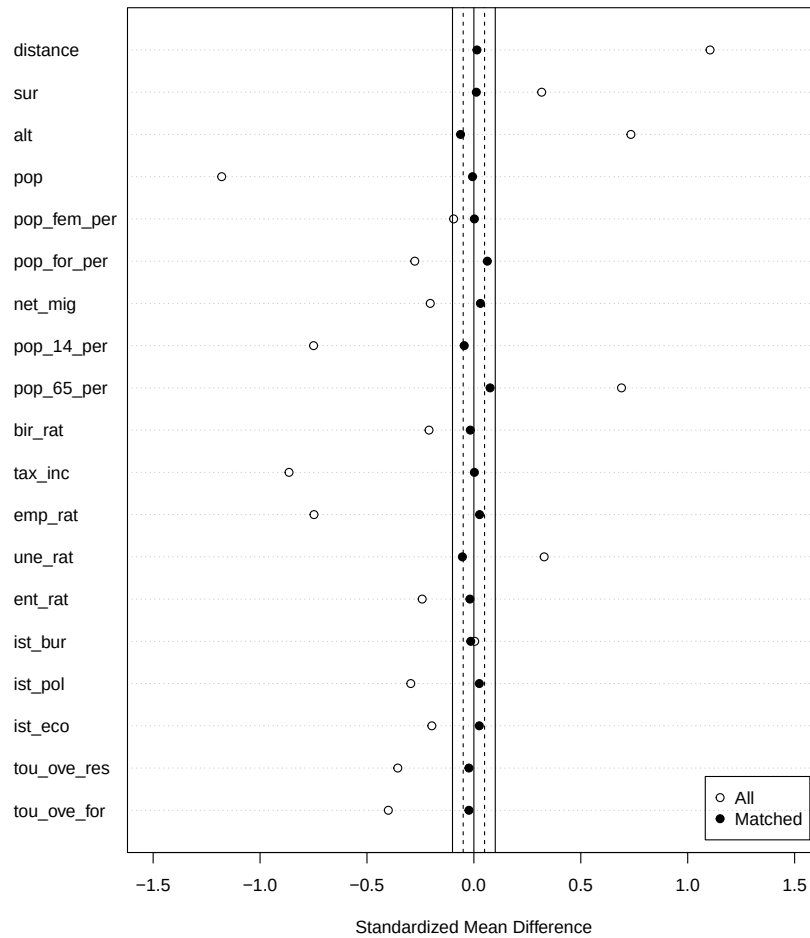


Figure A24: *Balancing graph before and after the PSM (model with belt municipalities)*

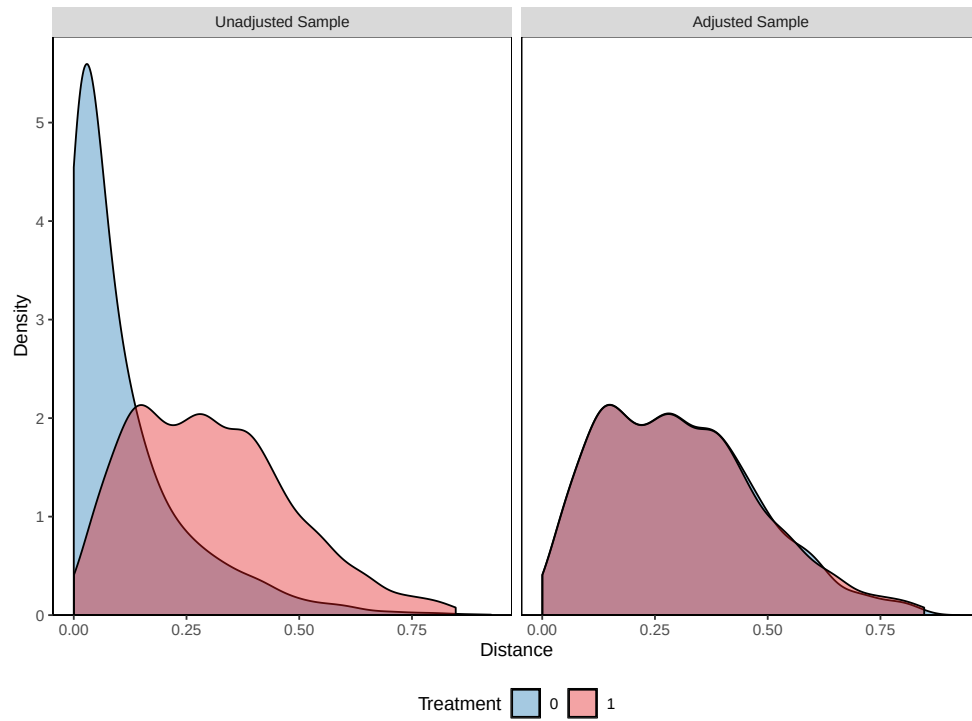
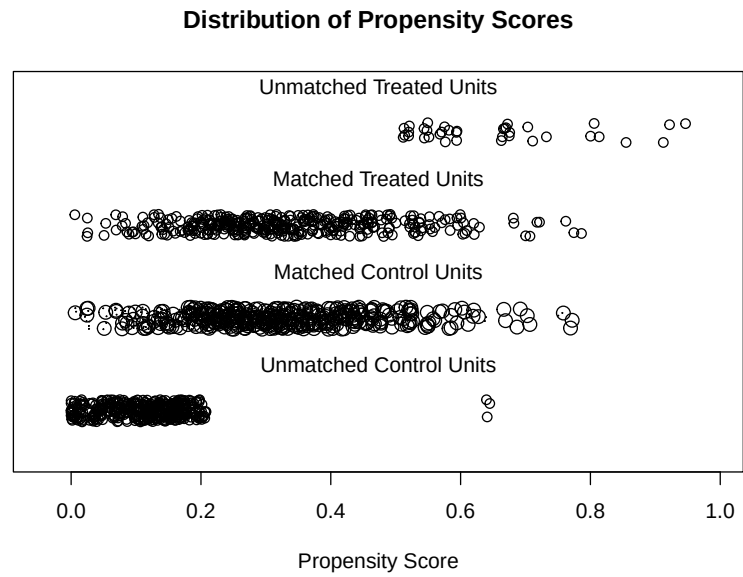


Figure A25: *Distribution of the PSM and common support (model with belt municipalities, North-Center regions)*



Group	Control	Treated
All	1,159	409
Matched (ESS)	373	372
Matched	772	372
Unmatched	367	37
Discarded	20	0

Figure A26: *Absolute standardized mean difference for covariates (model with belt municipalities, North-Center regions)*

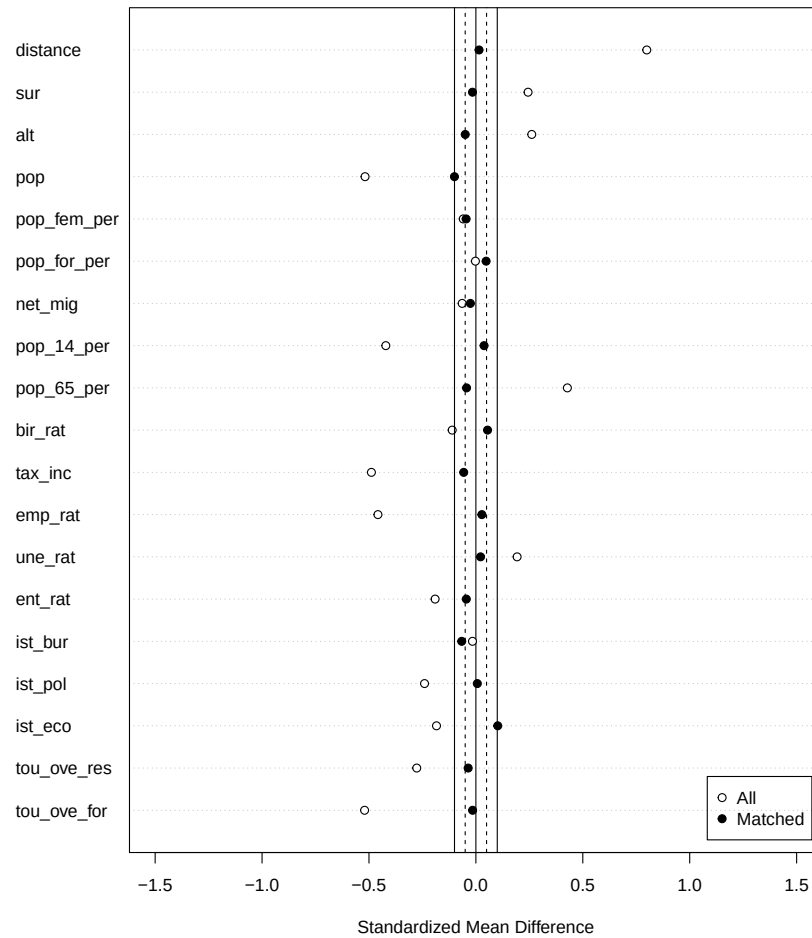


Figure A27: *Balancing graph before and after the PSM (model with belt municipalities, North-Center regions)*

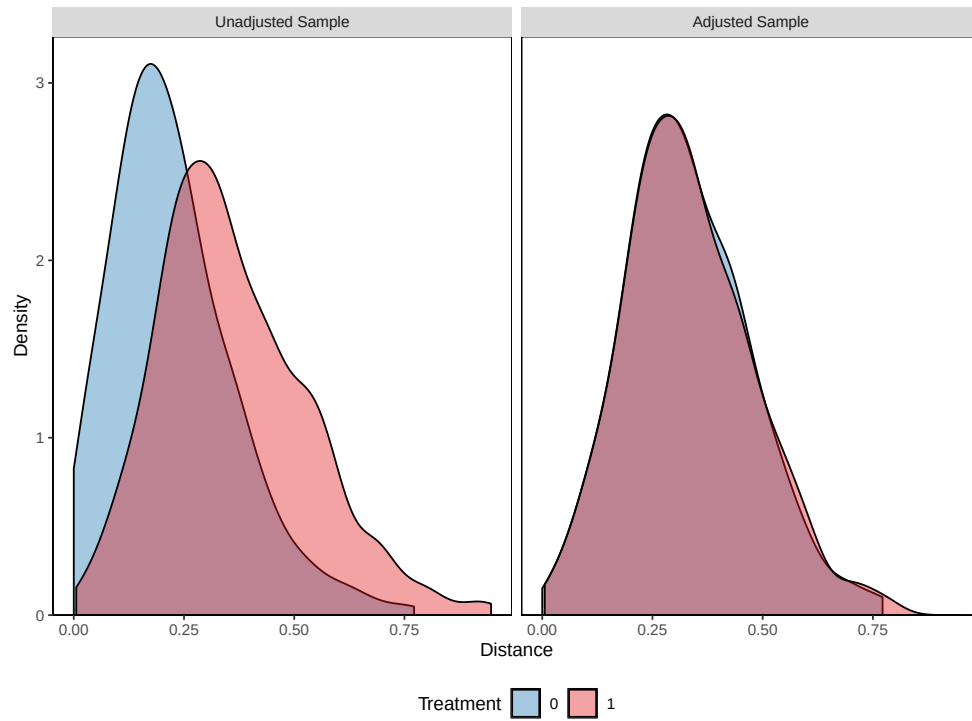
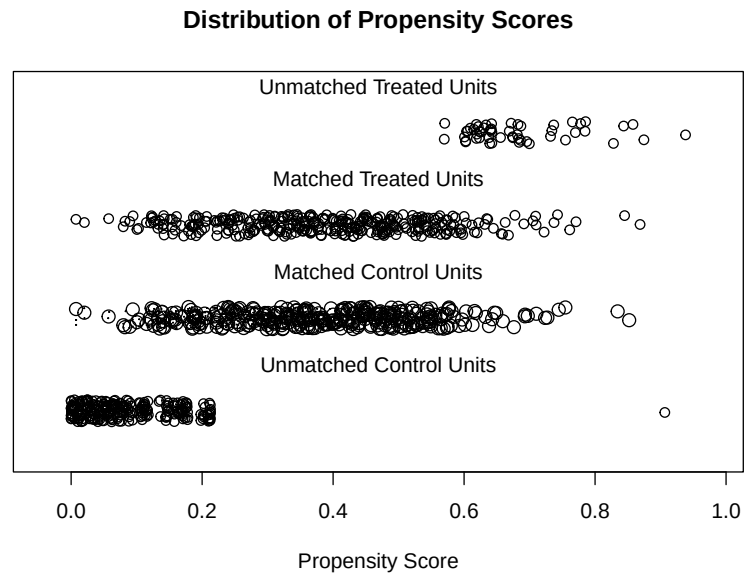


Figure A28: *Distribution of the PSM and common support (model with belt municipalities, South regions)*



Group	Control	Treated
All	888	398
Matched (ESS)	346	345
Matched	640	345
Unmatched	225	53
Discarded	23	0

Figure A29: *Absolute standardized mean difference for covariates (model with belt municipalities, South regions)*

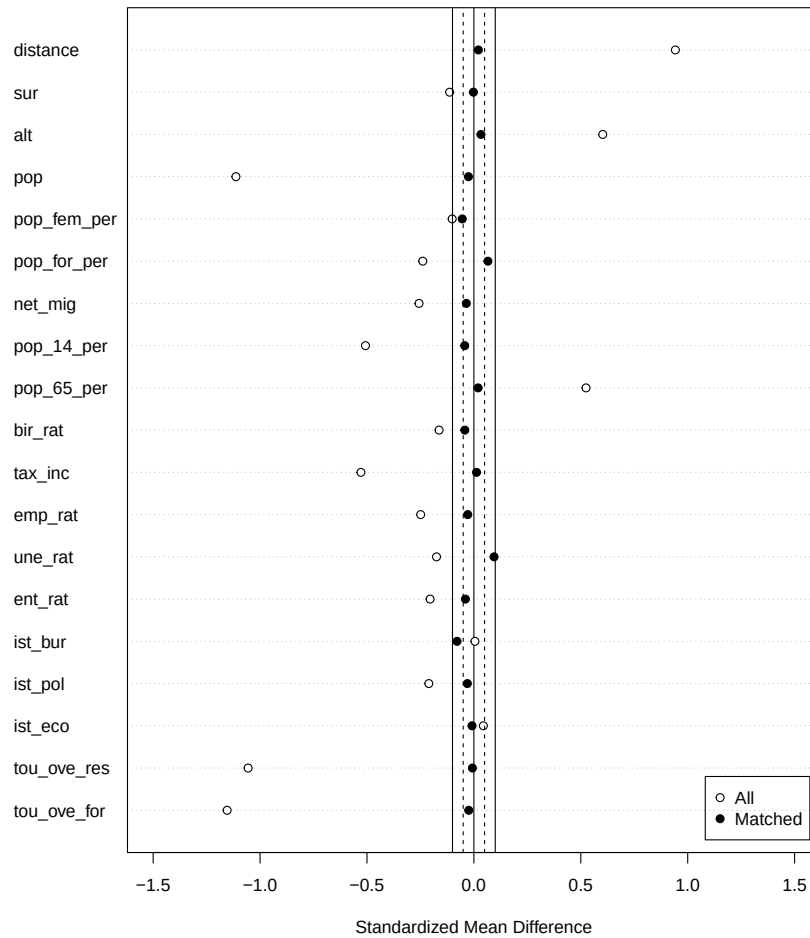


Figure A30: *Balancing graph before and after the PSM (model with belt municipalities, South regions)*

