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Research paper

The determinants of missed funding: Predicting the paradox of increased need and reduced allocation[☆]

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ABSTRACT

This research investigates how local governments overlook funding opportunities within the cohesion policies, utilizing machine learning and analysing data from open calls within the European Next Generation EU funds. The focus is on predicting which local governments may face challenges in utilizing available funding, specifically examining the allocation of funds for Italian childcare services. The results demonstrate that it is possible to make out-of-sample predictions of municipalities likely to abstain from invitations, by identifying key determinants. Population-related factors play an important role in predicting inertia, alongside other demand-related elements, particularly in regions with limited services. The study emphasizes the importance of local institutional quality and individual attributes of policymakers. The factors justifying fund allocation have adverse effects on participation, placing regions with greater investment needs at a competitive disadvantage. Anticipating non-participation in calls can aid in achieving policy targets and optimizing the allocation of funds across various local governments.

1. Introduction

Addressing regional disparities has been a persistent challenge, prompting various institutions, including the European Union, to develop comprehensive frameworks for cohesion policies over the years (Krugman, 1991; Farole et al., 2011). Within this context, there is a notable emphasis on place-based policies directed towards underdeveloped areas (Neumark and Simpson, 2015). The persistent struggle with regional disparities and the continuous discourse on the efficacy of these policies highlight the necessity for a nuanced comprehension of the factors shaping the distribution and utilization of funds.

From an empirical perspective, consensus regarding the efficacy of cohesion policies – those aimed at reducing regional disparities – remains elusive, given the divergence in results when considering different timeframes, territorial levels, and the use of various econometric methodologies (Mohl and Hagen, 2010; Becker et al., 2018).[1] Notably, recent times have witnessed a heightened focus on econometric research, driven by advancements in techniques and improved data accessibility. A meta-analysis by Dall'Erba and

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[1] We use 'cohesion policies' as a general term for redistributive regional policies. This term should not be confused with the specific 'Cohesion Policy' of the EU, though the EU Cohesion Policy is encompassed within our broader definition of cohesion policies.

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Fang (2017) illustrates that cohesion funds exhibit a generally positive and statistically significant impact on economic growth. Nevertheless, this impact is generally modest, especially when assessed concerning the resources allocated, and varies significantly across different countries (Bachtrögler et al., 2019). A notable example is Italy, which has implemented these policies since the post-World War II era, yet evaluation analyses provide scant empirical support for their ability to foster growth in the designated areas (Barone and de Blasio, 2023). Bronzini and De Blasio (2006) suggest that the initial effect of the funding is offset by a subsequent decline in the following years. However, Cerqua and Pellegrini (2014)'s analysis, which considers a more compelling evaluation strategy, reveals only a modest decline in the aftermath of the subsidy program. Regarding EU Cohesion Funds, while some positive influence is observed (Giua, 2017), it lacks durability (Barone and de Blasio, 2023). In the case of other programs, the impacts are confined to specific micro areas within underdeveloped regions, but these are offset by adverse effects in adjacent regions, an occurrence often referred to as spatial displacement, where the local economic boost draws resources from surrounding areas, reducing activity there (Andini and De Blasio, 2016).

The recent economic literature has shown that a significant aspect to consider is the role of local institutions, which play a crucial part in the multilevel governance characterizing place-based policies (Mendez and Bachtler, 2024). Analyses of government quality indicators reveal substantial regional variations in institutional quality (Charron et al., 2014). Given that a large share of cohesion initiatives are managed at the local government level, the quality of these local government institutions becomes important. To exemplify this, Becker et al. (2013), in their examination of European regions, demonstrate that institutional quality is a significant factor influencing the effectiveness of structural funds. Administrative capacity is also considered the dominant explanation of the deficiency in EU funds absorption (Incaltarau et al., 2020; Milio, 2007; Surubaru, 2017). Furthermore, local politicians wield a great influence in molding the distribution of financial resources (Van Wolleghem, 2022). Local governments that are politically aligned with central coalitions tend to receive more structural funds (Buscemi and Romani, 2022; Dotti, 2016). Additionally, local politicians' preferences significantly influence the allocation of cohesion funds, often directing investments towards areas that can enhance their public support (D'Amico, 2021; Van Wolleghem, 2022).

An unexplored aspect in the referenced literature is whether local beneficiaries – such as local governments or firms – might be reluctant to participate in competitive funding mechanisms, which typically constitute the standard approach to fund allocation. An aspect recently framed as a critical demand factor influencing absorption capacity and policy impact (Cunico et al., 2024). In practice, since many cohesion funds are distributed through open calls, when local governments, organizations, enterprises, or citizens choose not to participate, they forgo the possibility of competing for funding and miss the opportunity to advance their development initiatives. Within the EU cohesion policy framework, this is one of the reasons why several countries encountered difficulties in spending their allocated structural funds (European Parliament, 2011). Such suboptimal execution performance has been partially attributed to the quality of local governments, as indicated by their administrative capacity. Higher government quality is linked to better fund absorption, compliance, and goal achievement outcomes. In contrast, weaker administrative capacity often results in delays, non-compliance, and missed targets in policy implementation (Cunico et al., 2022; Mendez and Bachtler, 2024). This capacity is, in part, linked to the economic development levels of regions (Dincecco, 2017). Consequently, the limited allocation of funds is likely to have a more significant impact in territorial contexts where the imperative to invest is pronounced. This creates a paradox wherein the need for increased investment coexists with a reduction in resource allocation. In this context, empirical evidence suggests that regional policies often fail to achieve their objectives in the most underprivileged areas, largely because local governments possess comparatively limited planning capacities (Crescenzi and Giua, 2016; Kline and Moretti, 2014; Neumark and Simpson, 2015). If the goal of cohesion funds is to mitigate territorial inequalities, there is a risk of achieving the opposite outcome. This is especially true because the regions with greater needs might end up losing opportunities, thereby exacerbating disparities.

This paper investigates this aspect by leveraging one of the open calls of the Italian National Recovery and Resilience Plan (NRRP), which is the tool that outlines the objectives, reforms, and investments that Italy intends to implement through the European Next Generation EU funds.[2] We use a machine learning (ML) models to predict local governments that fail to seize funding opportunities, when such funding is needed, with a specific focus on the allocation of funds for childcare services within the Italian NRRP. Childcare is a particularly relevant area of study, as it is a widespread social issue essential for fostering inclusive growth, supporting families, and promoting labour market participation (Nollenberger and Rodríguez-Planas, 2015). Due to the heterogeneity in participation of local governing bodies (UPB - Parliamentary Budget Office, 2022), this serves as a case study on how and why potential beneficiaries, local administrations in our case, do not take advantage of available funding opportunities. Identifying in advance potential no-participants in the calls can serve as a valuable tool for national and European policymakers to improve funds' absorption.

From an empirical perspective, we align with recent economic literature suggesting that addressing policy problems, such as predicting which local governments may miss out on funding opportunities, requires more than standard regression techniques which were designed primarily to yield unbiased coefficient estimates rather than maximize prediction accuracy. In these cases, ML advancements offer particularly valuable tools (Kleinberg et al., 2015; Einav and Levin, 2014). ML techniques are gaining momentum for solving problems connected to poverty targeting (Jean et al., 2016), the effectiveness of public programs and spending (Andini et al., 2018), and to identify corruption and political connections (de Blasio et al., 2022; Mazrekaj et al., 2023). Focusing on the Italian context, recent works have leveraged the potential of ML to predict the bankruptcy of local governments (Antulov-Fantulin et al., 2021), vaccine hesitancy in municipalities (Carrieri et al., 2021), to estimate local mortality and local inequality during the COVID-19 pandemic (Cerqua et al., 2021; Cerqua and Letta, 2022), and to predict agri-food quality areas (Resce and Vaquero-Piñeiro,

[2] https://next-generation-eu.europa.eu/index_en; https://www.italiadomani.gov.it/content/sogei-ng/it/en/home.html.

2022).

Predicting local governments that are likely to miss out on funding opportunities could become a relevant tool for intervening in the inertia of local authorities that need services but do not compete. Our results show that it is possible to predict which local governments will not apply to the calls, and that territorial socioeconomic features matter. In particular, the population size and population density appear to be crucial for predicting the inertia of local governments. Other important factors are connected to the demand for the services such as female occupation rate and birth rate. Further analysis highlights the role of the local institutional quality, the income and education level of the resident population, and the individual characteristics of the policymakers such as age, seniority, and gender. The outcomes of this study offer valuable insights and policy recommendations for improving the allocation of funds to diverse local governments with varying needs.

The remainder of the paper is structured as follows, Section 2 presents the Institutional framework, Section 3 is dedicated to the data and the methods, Section 4 shows the results and Section 5 concludes.

2. Institutional framework

The Italian National Recovery and Resilience Plan provides additional and extraordinary financial resources to accomplish three main aims: to address the economic and social repercussions of the pandemic crisis; to drive a comprehensive ecological transition; and to tackle territorial disparities, gender inequality, weak productivity growth and a low rate of investment in human and physical capital. The third aim concerns the planning of the inclusion and cohesion mission.[3] Moreover, it planned to integrate Cohesion Policies with NRRP by ensuring that at least 40 percent of the resources are allocated to the Southern regions (Italian *Mezzogiorno*), the so-called "quota-sud".[4] Nevertheless, interventions were not planned based on a territorial mapping of investment needs and NRRP allocates most of the resources among territories through their participation in special calls for proposals that establish criteria for allocating resources in favour of participants on a competitive basis through submitting projects.

Among the scheduled initiatives, the NRRP allocates 4.6 billion Euros for the development of nursery schools and the expansion of school infrastructure. The goal is to enhance educational opportunities across the entire country by renovating existing nursery schools and constructing new ones. This effort aims not only to expand the availability and enhance the quality of these services but also to assist families in balancing their personal and professional lives, promoting gender equality and women's employment, and stimulating an increase in the birth rate. During the implementation phase, the distribution of NRRP funding designated for nursery schools has been structured using specific calls for proposals *"Bandi asili nido"*. These calls define the criteria for distributing resources to municipalities competitively, requiring them to submit projects for consideration. In a nation facing challenges related to declining birth rates and women's unemployment, the *"Bandi asili nido"* program becomes an important element within the context of the Italian NRRP. Extensive research demonstrates that childcare for preschool-aged children has a beneficial effect on maternal employment, especially among specific subgroups such as single mothers or those residing in economically disadvantaged areas (Lefebvre and Merrigan, 2008; Baker et al., 2008; Cascio, 2009; Fitzpatrick, 2010; Goux and Maurin, 2010; Havnes and Mogstad, 2011; Nollenberger and Rodríguez-Planas, 2015; Carta and Rizzica, 2018). Furthermore, in 2022, during the European Council meeting in Barcelona, it was mandated that Member states should strive to provide childcare services for at least 33 percent of children under 3 years old (Barcelona, 2002). Then, after the Covid-19 emergency, both objectives were updated.[5]

In this context, Italy integrated the 33 percent objective into national legislation (Dlgs 65/2017), underlying the need to reduce territorial imbalances in the offer of early childhood services. Italy shows significant territorial inequalities in the availability and quality of childcare services, as depicted in Fig. 1(a) where southern and more peripheral areas suffer a lack of adequate childcare services and are far from achieving the objective set at 33 percent of the number of nursery places for 100 children aged 0–2, hereafter LEP, i.e., essential levels of performance and services.[6] In particular, the national mean for the municipal service coverage is around 16 nursery places for 100 children aged 0–2, in southern municipalities the mean is around 9 for 100 children aged 0–2, and in the municipalities of centre-north the mean is around 19 for 100 children aged 0–2.[7] Variations exist among regions, with none, on the average of municipal coverage, meeting the 33 percent threshold. Additionally, when examining provinces (NUTS3 level), it becomes evident that only municipalities in eight provinces (one in Lombardy, one in Friuli-Venezia Giulia, two in Emilia-Romagna, and four in Tuscany) surpass the specified threshold on average.[8]

In this framework, the NRRP resources are a unique opportunity to fill territorial gaps. Through Investment 1.1 (Plan for nurseries and nursery schools and early childhood education and care services) of Component 1 (Strengthening the offer of education services:

[3] NRRP plans the investment in six thematic areas, the so-called missions, i.e., digitization, ecological transition, sustainable infrastructure, education and research, inclusion and cohesion, and health.

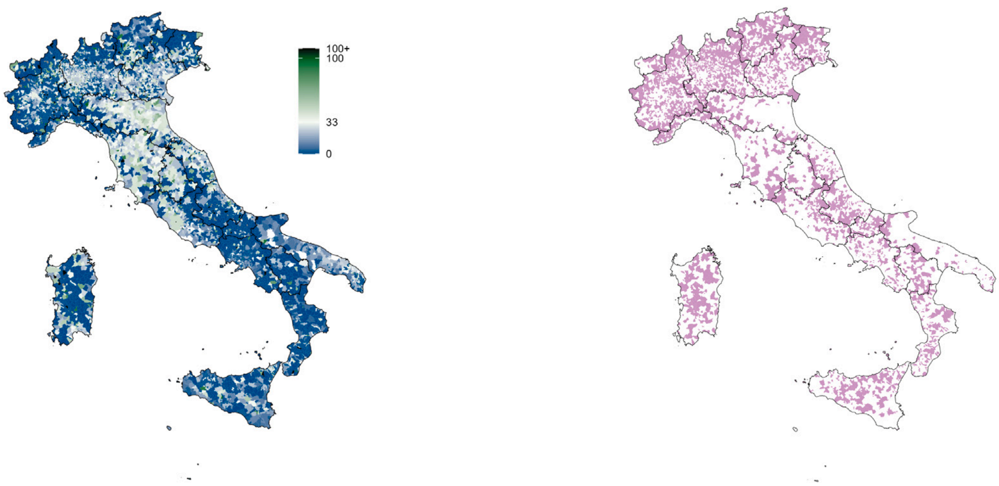
[4] Southern Italy, also known as *Meridione* or *Mezzogiorno* comprises the administrative regions that correspond to Abruzzi, Apulia, Basilicata, Calabria, Campania, Molise, Sicily, and Sardinia.

[5] A resolution of the EU Council of February 2021, has raised the objective of 90 percent in the 3–5 year age group to 96 percent, and the target of 33 percent for the under 3 age group to 45 percent, as part of the education targets to be achieved by 2030.

[6] Source for Nursery schools coverage rate: Istat

[7] If we sum the supply of places both in nursery schools and in supplementary early childhood services, the average municipal coverage is around 21 places for 100 children aged 0–2, 14 for the south and 25 for the centre and north. Note that, as reported by UPB - Parliamentary Budget Office (2022), the sum of available places divided by the total number of children 0–2 in Italy is 26.9, the lower level of the figures reported here (the average of municipal coverage) depends on the fact that many (small) municipalities have small or zero coverage.

[8] If we sum the supply of places both in nursery schools and in supplementary early childhood services, we find 17 provinces with an average of municipal coverage more than 33 places for children aged 0–2.



(a) Nursery places for 100 children aged 0-2 years in Italian municipalities in 2020

(b) Municipalities with a LEP less or equal to 33 that did not participate in the "Bandi asilo" call

Fig. 1. Territorial distribution of nursery places and target municipalities.

from nurseries to universities) of Mission 4 (Education and Research), Italy assigns around 3.7 billion Euro for the creation of new spaces in early childhood education and care services through two distinct procedures. The first, as mentioned, pertains to ongoing projects totalling 0.7 billion Euros and was initiated with the DPCM (Decree of the President of the Council of Ministers) on December 30, 2020. The second, concerning the NRRP funds of 3 billion Euros, was initiated through a public notice on December 2, 2021 by the Ministry of Education.[9] Both the December 30 DPCM and the December 2021 public notice establish special calls for proposals open to all Italian municipalities, either individually or in partnership with other municipalities. To address economic and social imbalances, the former official measure aims to allocate 60 percent of the funds for structures in disadvantaged areas and urban suburbs, identified by the social and material vulnerability index (IVSM) calculated by Istat. The latter official measure, financed with NRRP resources, envisaged two constraints: the previously mentioned *"quota-sud"* and the consideration of the coverage rate at the regional level. However, different from the call of DPCM in December 2020, in which the requests were better than expected, for the NRRP one there was a poor response, particularly from southern municipalities. Subsequently, there was a further call only destined for the Mezzogiorno regions, with a priority for municipalities located in Basilicata, Molise, and Sicily.

This framework adopts a two-stage approach to simultaneously foster municipal autonomy and ensure alignment with NRRP goals. In the first stage, municipalities can independently propose or partner on projects through competitive calls for proposals. In the second stage, resources are allocated based on territorial eligibility criteria included in the calls—thereby guaranteeing that the final distribution of funds remains consistent with NRRP objectives. However, it did not seem to work because around 60 percent of municipalities with coverage less than or equal to 33 percent did not participate in the calls for proposals. UPB - Parliamentary Budget Office (2022) highlight that over 3400 municipalities with a serious shortage of nursery schools (coverage rate below 11) did not participate in the *"Bandi asili nido"* calls. Fig. 1(b), shows the municipalities with coverage less than or equal to 33 which did not participate in either of the two calls for proposals.[10] The Centre-North's performance might appear comparatively weaker, but this can be partly explained by the fact that there was only one call available for these regions, whereas the call in the South was reopened, offering local administrations there an additional opportunity to apply for funds. This distinction highlights the importance of considering the unique circumstances in each area. This paper explores whether it is possible to predict which municipalities are likely not to apply to the call, even when they need to, and what the main determinants of this inertia are.

3. Data and method

3.1. Data

Our sample includes all 6465 municipalities that have a number of nursery places for 100 children aged 0–2 equal to or less than 33. We perform two different predictions, one for Southern regions and one for the rest of the Country (Centre-North). The former

[9] 2.4 billion for nursery schools, i.e., 0–2 years and 0.6 for schools of childhood, i.e., 3–6 years.

[10] The pink points represent municipalities with coverage of 33 or less that did not participate in either of the two calls for proposals. The white areas indicate municipalities with coverage of 33 or less that participated in at least one of the calls, as well as municipalities with coverage exceeding 33.

includes 2274 municipalities while the latter includes 4191. Two primary issues affected this decision: firstly, the NRRP imposes an allocation constraint known as the abovementioned *"quota-sud"* which mandates that 40 percent of the funding must be directed towards the southern regions; secondly, the reopening of the *"Bandi asili nido"* call exclusively for southern regions (see Section 2), such that ultimately, non-application rates appear to be higher in the Centre-North compared to the South (see Table 1). These contribute to a scenario where, in practice, two distinct competitions have emerged in different parts of the country.

Our dependent variable is the non-application to at least one call *Bandi asilo* that is equal to 1 if the municipality did not apply for the part of the call referred to the nursery school for children 0–2 years for any call, and 0 otherwise. We identify five categories of predictors that could potentially influence non-application and, consequently, local government inertia: population (Pop), socioeconomic (SE), demand (D), institutions (IQ), and politics (Pol).[11] All features are taken in the period before the call opening.[12] In Table A.1 in the Appendix, we show the source of data and the year of reference.

The population features include total population, population 0–2, and population density. The total population and the 0–2 age group reflect the demographic composition, and population density captures the dynamics, which are also strongly connected to urbanization — an indicator that has been recognized as crucial for the effectiveness of the cohesion policy.[13]

The socio-economic features consist of the proportion of the population with a degree and income as drivers of the development of territories but are also strictly correlated to the demand features of territories. Particularly, education levels may serve as a proxy for the community's overall capacity to engage with and leverage public opportunities, as higher educational attainment is often associated with better resource management and a reduced likelihood of missing out on funding opportunities. Income levels, on the other hand, can reflect a community's development status but may also have more complex implications with public service demand.

To directly consider the demand features, we consider the proportion of foreigners, the proportion of the population 20–49, the proportion of the population over 70, the birth rate, the proportion of female occupation, the proportion of families with 3 components or more, and the nursery schools coverage rate. In particular, foreign populations are more likely to use services such as daycare, as they are often less likely to have family networks nearby to assist with childcare, and may therefore rely more heavily on formal childcare services. The proportion of the population aged 20–49 is included as this age group typically represents working-age adults who are most likely to have young children in need of care. Conversely, the proportion of the population over 70 reflects potential intergenerational dynamics, as older family members often provide informal childcare support. The proportion of female occupation is a critical factor, as higher employment rates among women often increase the demand for formal childcare services to enable workforce participation. The birth rate is a direct indicator of potential childcare needs, as higher birth rates are associated with a greater number of young children requiring care. Similarly, families with three or more members are more likely to have children and thus have a higher need for such services. Finally, the nursery school coverage rate captures the availability of existing childcare infrastructure, which directly impacts the accessibility of services and may influence demand levels. These factors have a dual role because, on the one hand, they could drive call participation by indicating a need to address an already existing demand in the territory; on the other hand, they can reflect an opportunity to invest in the territory, fostering confidence in its potential and stimulating future demand. For instance, a wise mayor, even in the face of a lack of children, could proactively implement policies such as building a new nursery school to increase the birth rate and attract families to the area.

The institutional features that can be connected to local government inertia in leveraging and managing funding opportunities include the proportion of municipal employees with a degree or more, technical office expenses[14] and the provincial institutional quality index (Nifo and Vecchione, 2014) with its five components, i.e., Regulatory quality, Government Effectiveness, Rule of law, Corruption, Voice and accountability.[15]

To conclude, the political features include the human capital of policy-makers and their attitudes to understanding decision-making and answering territorial needs. Politicians who are better equipped to navigate the intricacies of policy-making, financial management, and resource allocation, are more adept at identifying available funding sources, developing competitive grant proposals, and effectively managing funds once secured. The factors we include are the average age of both the municipal council and the assessors, the percentage of females of both the municipal council and the assessors, the age, gender, and education of the mayor, the seniority of the mayor (years in charge), and the political party position. Even if these factors do not directly measure the competencies of local politicians, they are proxies for experience, diversity, and the skill set within the municipal

[11] Notice that this division in categories has no direct implications for the estimation results, as it is simply a tool for organizing the variables and providing a clearer analytic framework.

[12] Data on administrators in office as of December 31, 2021, were used for the analysis. The dataset was filtered based on election dates to exclude municipalities where mayors were not in office during the 2020–2021 period. Only municipalities with mayors who had been in office since at least 2019 were included, ensuring the focus remained on political variables that may have influenced the likelihood of applying to the calls.

[13] Population aged 0–2 is classified as a population factor (not demand) to capture key demographic characteristics of the area and provide context for its overall population composition. This classification does not directly influence the model's estimation results but serves to organize variables based on their structural relevance. Instead, the birth rate is included among the demand factors, as it more directly reflects potential childcare needs.

[14] Technical office expenses include expenses for authorization acts, oversight and control activities, occupancy certifications, and the planning and coordination of public works. Additionally, it covers expenditures for institutional facilities, municipal offices, and certain monuments under municipal jurisdiction that are not classified as cultural heritage. We used the absolute value to capture the actual resources available, thus providing a direct measure of administrative capacity.

[15] Voice and Accountability indicates the degree of citizens' participation in social and public life and processes set up to select the governing class; the Government Effectiveness is quality of public service and the policies formulated and implemented by the local government; the Regulatory Quality represents the ability of government to promote and formulate effective regulatory interventions; the Rule of Law is the perception concerning law enforcement both in terms of contract fulfilment, property rights, police forces, activities of the magistracy and crime levels; the Control and Corruption indicates the degree of corruption of those performing public functions both in terms of illegal gains and private proceeds acquired to the detriment of society.

Table 1
Descriptive statistics.

	South		Centre-North	
	Mean	sd	Mean	sd
Non-application	0.46	0.50	0.69	0.46
Population (Pop)				
Total population (inhabitant)	8006.27	29,313.08	5722.74	25,462.99
Population 0–2 (inhabitant)	174.42	672.35	117.45	530.17
Population density (inhabitants per km^2)	300.02	835.48	281.05	506.99
Socioeconomic (SE)				
Income (EUR per capita)	19,867.90	2421.53	23,555.41	2728.91
Share of population with degree or more (%)	0.04	0.02	0.04	0.01
Demand (D)				
Share of foreign population (%)	0.04	0.03	0.08	0.04
Share of population 20–49 (%)	0.36	0.03	0.34	0.04
Share of population over 70 (%)	0.19	0.05	0.19	0.05
Birth rate (live births per 1000 inhabitants)	6.55	2.64	6.30	2.88
Female's occupation rate (%)	0.39	0.07	0.57	0.07
Share of families with 3 components or more (%)	0.37	0.08	0.34	0.08
Nursery schools coverage rate (places per 100 children aged 0–2)	3.86	7.90	7.59	11.11
Institutional (IQ)				
Share of municipal empl. with a degree or more (%)	0.77	0.19	0.81	0.17
Technical offices expenditure (EUR)	336,942.01	4,827,467.82	234,868.10	859,467.86
Institutional Quality Index (index, 0–1)	0.33	0.14	0.74	0.13
Corruption (index, 0–1)	0.59	0.16	0.91	0.06
Government effectiveness (index, 0–1)	0.29	0.13	0.46	0.14
Regulatory quality (index, 0–1)	0.28	0.18	0.57	0.14
Rule of law (index, 0–1)	0.33	0.18	0.72	0.16
Voice and accountability (index, 0–1)	0.39	0.18	0.64	0.10
Politics (Pol)				
Average age of the council (years)	47.23	4.15	50.02	4.74
Share of females in the council (proportion)	0.31	0.13	0.34	0.12
Average age of assessors (years)	48.34	5.85	52.01	7.16
Share of females among assessors (%)	0.31	0.17	0.33	0.18
Mayor's age (years)	53.42	10.40	54.75	11.32
Mayor's education (binary, 1 = degree or more)	0.63	0.48	0.40	0.49
Female Mayor (binary, 1 = female)	0.09	0.29	0.17	0.37
Seniority of the Mayor (years)	1.85	1.38	1.80	1.05
Political Party				
N	2274		4191	

Note: IQ indices range from 0 to 1, with higher values indicating better quality. The variable for political party is not converted into numeric codes; instead, it is grouped into three categories—"civic list", "right", and "left".

leadership. These may influence local politicians' preparedness to engage with complex administrative tasks and their responsiveness to local needs. For example, average age can be indicative of the tendency of younger politicians to behave strategically, increasing spending and obtaining more transfers; gender diversity may reflect varying perspectives, mainly concerning people's well-being. The mayor's education could represent a relevant skill set, particularly for administrative and managerial challenges, while political party orientation might suggest specific policy inclinations that impact engagement levels. Finally, seniority could be indicative of a politician's capacity to navigate complex initiatives over time, balancing initial inexperience with growing familiarity with administrative processes and the ability to strategically time their actions to align with electoral cycles and project completion timelines.

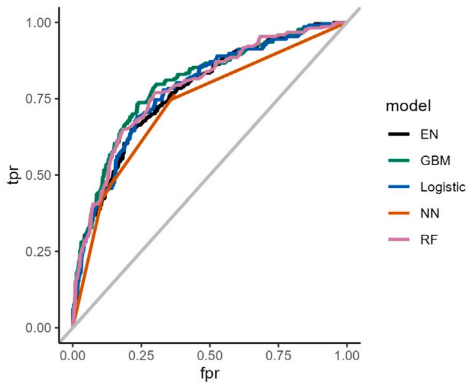
Table 1 reports the descriptive statistics for each predictor in the two subsamples.[16]

3.2. Method

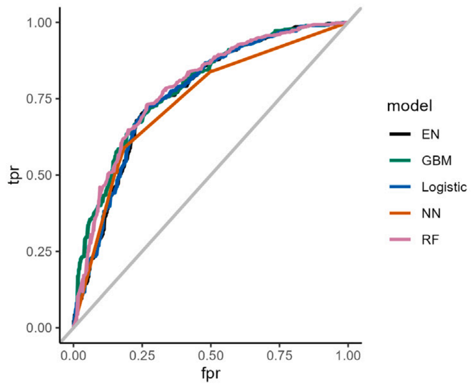
The prediction task is formulated as follows, for each municipality i at the year t, based on the set of lagged features $\{Pop, SE, D, IQ, Pol\}_{i,t-1}$, find the function $f(.)$ (machine learning model) that predicts non-application to at least one call *Bandi asilo* ($NoApp_{i,t}$):

$$\{Pop, SE, D, IQ, Pol\}_{i,t-1} \xrightarrow{f(.)} NoApp_{i,t}. \quad (1)$$

[16] Several standard deviations (SD) are much larger than the mean, which suggests potential skewness in the data. We do not address this issue explicitly, as the analysis relies on various machine learning algorithms, such as Gradient Boosting Machines and Random Forests, which are robust to non-normal distributions and do not require the data to follow specific statistical assumptions.



(a) South



(b) Centre-North

Fig. 2. ROC curves. Models trained on 80 percent of observations and tested on the remaining 20 percent. The ROC curves are calculated on the test set (20 percent of the data, the same for each algorithm). Average (out of 10 splittings) AUC South: EN = 0.745, RF = 0.758, GBM = 0.769, NN = 0.745, Logistic = 0.746. Average (out of 10 splittings) AUC Centre-North: EN = 0.756, RF = 0.766, GBM = 0.767, NN = 0.722, Logistic = 0.757.

Following the predominant approach in the literature using ML models in social science, we randomly divide the database as 80 percent for training and 20 percent for the out-of-sample testing set. Because various data splits can yield varying outcomes, we conducted ten distinct random data splits and calculated the average out-of-sample model performance across these iterations to enhance the stability of our results.

We use four different ML predicting algorithms plus a more "classical" logistic regression model:

- Elastic Net (EN): a regression statistical method that performs features selection and regularization with a mix of L1 (LASSO-type) and L2 (ridge-type) penalization to reduce over-fitting and increase prediction accuracy and interpretability (Tibshirani, 1996; Zou and Hastie, 2005);
- Random Forest (RF): a family of randomized tree-based classifier decision trees that uses different random subsets of the features at each split in the tree (Breiman, 2001);
- Gradient Boosting Machines (GBM): an ensemble method that works in an iterative way where at each stage new learner tries to correct the pseudo-residual of its predecessors (Friedman, 2001);
- Neural Network (NN): a model that uses a set of connected input/output units in which each connection has an associated weight, and learns by adjusting the weights to predict the correct class label of the given input (Ripley et al., 2016).

The hyper-parameter optimization is only done on the training set using a repeated (10 times) five-fold cross-validation.[17] The performance of non-application classification prediction is assessed by analysing the Receiver Operating Characteristics curve (ROC) (Fawcett, 2006) on the test set. In our binary classification problem, the positive class is defined as the municipality that does not apply to the call, and the negative class is the municipality that applies to the call. The ROC curve shows the classifier's diagnostic ability by plotting the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis, since its discrimination threshold is varied (Antulov-Fantulin et al., 2021). When the classification task is completely unpredictable, the ROC curve is the diagonal line with an Area Under the Curve (AUC) of 0.5; a perfect classifier, instead, has AUC equal to 1.0, overall, the higher the AUC, the more predictive the model.

4. Results

In this section, we present the results of the model predicting local governments that miss out on funding chances. The focus will be on two main aspects: the predictability of our dependent variable (Section 4.1) and the features' importance of independent variables used for predictions (Section 4.2).

4.1. The prediction task

This section shows the out-of-the-sample performance of the models after the hyper-parameter optimization performed on the training set.[18] The AUC in Fig. 2 shows that the GBM models outperform all the other ML models, while other algorithms, as well as the Logistic regression, show slightly lower performance both in the Southern and Centre-North regions. This aligns with

[17] All models have been implemented using R software trained with the optimisation algorithms available through the `caret` package (Kuhn, 2021).

[18] In the case of Southern regions the hyperparameters best tune for EN is alpha = 1 and lambda = 0.0002819956; for Random Forest is mtry (Number of variables available for splitting at each tree node) = 2; for Gradient Boosting Machine is n.trees (total number of trees to fit) = 100, interaction.depth (number

Table 2
Results of DeLong's test for ROC curves.

	South		Centre-North	
	Z	*p*-value	Z	*p*-value
GBM vs. RF	1.323	0.344	0.219	0.462
GBM vs. EN	1.784	0.133	1.158	0.248
GBM vs. NN	3.881	0.031	4.008	0.004
GBM vs. Logit	1.724	0.142	1.076	0.269

Averages calculated across the repetitions for 10 different random splittings.

Table 3
Models' performances.

	South					Centre-North				
	GBM	RF	EN	NN	Logit	GBM	RF	EN	NN	Logit
Accuracy	0.701	0.694	0.659	0.677	0.679	0.748	0.755	0.726	0.745	0.747
Kappa	0.391	0.379	0.318	0.348	0.353	0.334	0.350	0.287	0.303	0.308
AccuracyLower	0.656	0.649	0.613	0.631	0.634	0.717	0.724	0.695	0.714	0.716
AccuracyUpper	0.743	0.737	0.703	0.720	0.722	0.777	0.784	0.756	0.775	0.776
AccuracyNull	0.546	0.546	0.546	0.546	0.546	0.693	0.693	0.693	0.693	0.693
AccuracyPValue	0.000	0.000	0.004	0.000	0.000	0.005	0.000	0.088	0.004	0.003
McnemarPValue	0.285	0.329	0.155	0.621	0.656	0.000	0.000	0.102	0.000	0.000
Sensitivity	0.625	0.626	0.645	0.647	0.646	0.907	0.914	0.861	0.928	0.929
Specificity	0.764	0.751	0.674	0.701	0.707	0.391	0.396	0.415	0.332	0.336
Pos Pred Value	0.688	0.677	0.646	0.643	0.647	0.771	0.774	0.776	0.758	0.760
Neg Pred Value	0.710	0.707	0.709	0.705	0.706	0.651	0.671	NA	0.673	0.677
Precision	0.688	0.677	0.646	0.643	0.647	0.771	0.774	0.776	0.758	0.760
Recall	0.625	0.626	0.645	0.647	0.646	0.907	0.914	0.861	0.928	0.929
F1	0.654	0.650	0.625	0.644	0.646	0.833	0.838	0.812	0.835	0.836
Prevalence	0.454	0.454	0.454	0.454	0.454	0.693	0.693	0.693	0.693	0.693
Detection rate	0.284	0.285	0.292	0.294	0.294	0.629	0.634	0.598	0.644	0.644
Detection prevalence	0.413	0.420	0.471	0.457	0.454	0.816	0.819	0.776	0.849	0.848
Balanced accuracy	0.694	0.689	0.660	0.674	0.676	0.649	0.655	0.638	0.630	0.633

Figures are estimated on the confusion matrix, which shows a cross-tabulation of the observed and predicted classes, generating the predicted classes based on the typical 50 percent cutoff for the probabilities (Kuhn, 2021). Averages were calculated across the repetitions for 10 different random splittings.

previous empirical applications, confirming that the tree-based models are the more competitive methods for structured binary tasks, especially for municipality classifications (Antulov-Fantulin et al., 2021; Carrieri et al., 2021; Resce and Vaquero-Piñeiro, 2022). However, the results of the DeLong et al. (1988)'s statistical test in Table 2 suggest that, for both the South and Centre-North cases, the difference between the ROC curve of the GBM model (the top-performing one) and the remaining models is statistically meaningful (p-value < 0.05) solely in the case of the NN model. Consequently, the performance of RF, EL, and Logit appears to be comparable to that of the GBM model. It is important to note that the comparable performance of logistic regression to more complex algorithms does not undermine our empirical ML framework, which incorporates lagged features, train-test splitting, and out-of-sample validation. This approach enables us to robustly validate logistic regression's out-of-sample performance, providing a comparative perspective across algorithms. Additionally, the other algorithms tested – particularly the best performer, GBM – offer further benefits such as greater flexibility, adaptability to diverse patterns, and the ability to detect complex relationships, as further illustrated in the partial dependence plots in Section 4.2.

Given the relevance of these features to our problem, GBM demonstrates superior performance across critical classification metrics (AUC in Fig. 2).

Moreover, the GBM prediction capabilities are particularly evident when performing a single predictive exercise using all municipalities without splitting into South and Centre-North regions. Results in Tables 5 and 4 confirm that good predictive performance can also be achieved in this case, especially with GBM, which outperforms Logit and other algorithms (except RF) according to the DeLong test (DeLong et al., 1988). This approach yields results that are more generalizable and less structured, providing broader applicability. In this context, GBM outperforms parametric tools, demonstrating its value for capturing intricate patterns that logistic regression may overlook. Such capabilities are particularly relevant when designing an early warning tool, where generalizability and adaptability to diverse scenarios are crucial. These findings underscore the potential of GBM to generate actionable insights that can inform policy interventions across diverse geographical contexts.

of splits in each tree) = 1, shrinkage (learning rate) = 0.1, and n.minobsinnode (minimum number of observations in terminal nodes) = 10; and for Neural Network is size (number of units in the hidden layer) = 3, decay (parameter for weight decay) = 0.1. In the case of Centre-Northern regions the hyperparameters best tune for EN is alpha = 1 and lambda = 0.0002897591; for Random Forest is mtry = 2; for Gradient Boosting Machine is n.trees = 100, interaction.depth = 2, shrinkage = 0.1, and n.minobsinnode = 10; and for Neural Network is size = 5, decay = 0.1.

Table 4
Results of DeLong's test for ROC curves using all sample.

	Z	*p*-value
GBM vs. RF	0.768	0.426
GBM vs. EN	2.664	0.042
GBM vs. NN	8.004	0.000
GBM vs. Logit	2.596	0.048

Averages calculated across the repetitions for 10 different random splitting. AUC: 0.789 GBM; 0.785 RF; 0.771 EN; 0.707 NN; 0.772 Logistic.

Table 5
Models' performances using all sample.

	GBM	RF	EN	NN	Logit
Accuracy	0.730	0.731	0.682	0.716	0.716
Kappa	0.413	0.415	0.299	0.369	0.371
AccuracyLower	0.705	0.706	0.656	0.690	0.691
AccuracyUpper	0.754	0.755	0.707	0.740	0.741
AccuracyNull	0.611	0.611	0.611	0.611	0.611
AccuracyPValue	0.000	0.000	0.019	0.000	0.000
McnemarPValue	0.002	0.000	0.007	0.000	0.000
Sensitivity	0.835	0.836	0.814	0.860	0.859
Specificity	0.566	0.567	0.473	0.490	0.492
Pos Pred Value	0.751	0.752	0.716	0.726	0.726
Neg Pred Value	0.686	0.687	0.659	0.691	0.691
Precision	0.751	0.752	0.716	0.726	0.726
Recall	0.835	0.836	0.814	0.860	0.859
F1	0.790	0.791	0.753	0.787	0.787
Prevalence	0.611	0.611	0.611	0.611	0.611
Detection rate	0.510	0.510	0.498	0.526	0.525
Detection prevalence	0.679	0.679	0.703	0.724	0.723
Balanced accuracy	0.700	0.701	0.644	0.675	0.676

Figures are estimated on the confusion matrix, which shows a cross-tabulation of the observed and predicted classes, generating the predicted classes based on the typical 50 percent cutoff for the probabilities (Kuhn, 2021). Averages were calculated across the repetitions for 10 different random splittings.

The satisfactory performance of all the algorithms presented here is proven by the high level of accuracy, statistically higher than the no information rate, and the high level of all the other performance measures reported in Table 3. In terms of Cohen's Kappa, Table 3 shows that all models (except the Elastic Net for the Centre-North) have values higher than 0.3 and close to 0.4 in the case of GBM both in the Southern and Centre-North municipalities, figures which are in the range between 'fair' and 'moderate' strength of agreement about the prediction reliability (Altman, 1990; Landis and Koch, 1977). In terms of the *P*-value of [Accuracy > Accuracy Null (No Information Rate)], all models in any area have an accuracy statistically higher than the no information rate, except the Elastic Net in centre-northern regions (*P*-value = 0.115). Table 3 also reveals performance differences between the northern and southern samples. These differences are reflected in the ranking of algorithms, with GBM achieving higher accuracy in southern municipalities and RF performing better in northern municipalities. Furthermore, in terms of accuracy, Table 3 also shows that the Logistic regression exhibits good performances overall. This result aligns with studies showing that, in certain binary cases, simple logistic regression performs well (Christodoulou et al., 2019). While we rely solely on AUC for the following steps, as it considers the trade-offs between precision and recall (whereas accuracy only measures the proportion of correct predictions), it is worth noting that this variation may primarily stem from two key factors. First, the NRRP funding includes a 40 per cent quota specifically allocated to southern regions, and the call was reopened exclusively for southern regions with low application rates in the initial round (see Section 2). This creates distinct competitive environments that may influence prediction performance and highlight local factors linked to non-application. Second, there are well-documented structural differences between northern and southern regions, particularly in public sector performance (Agasisti and Porcelli, 2023; Lagravinese et al., 2019; Antulov-Fantulin et al., 2021). Both these factors likely contribute to the observed differences and will be further investigated in Section 4.2.

Overall, the results in this section clearly show that the inertia of local government in being engaged in cohesion calls can be predicted with almost all the ML algorithms available in the literature.

4.2. The determinants of inertia

This section presents an elaboration of the feature's importance in the prediction of the inertia of local governments. In this task, we used the GBM, which is the model with the higher area under the ROC curves (see Fig. 2). To maximize the utilization of available data for the analysis presented in this section, we retrained the GBM model on the entire dataset using the hyperparameters

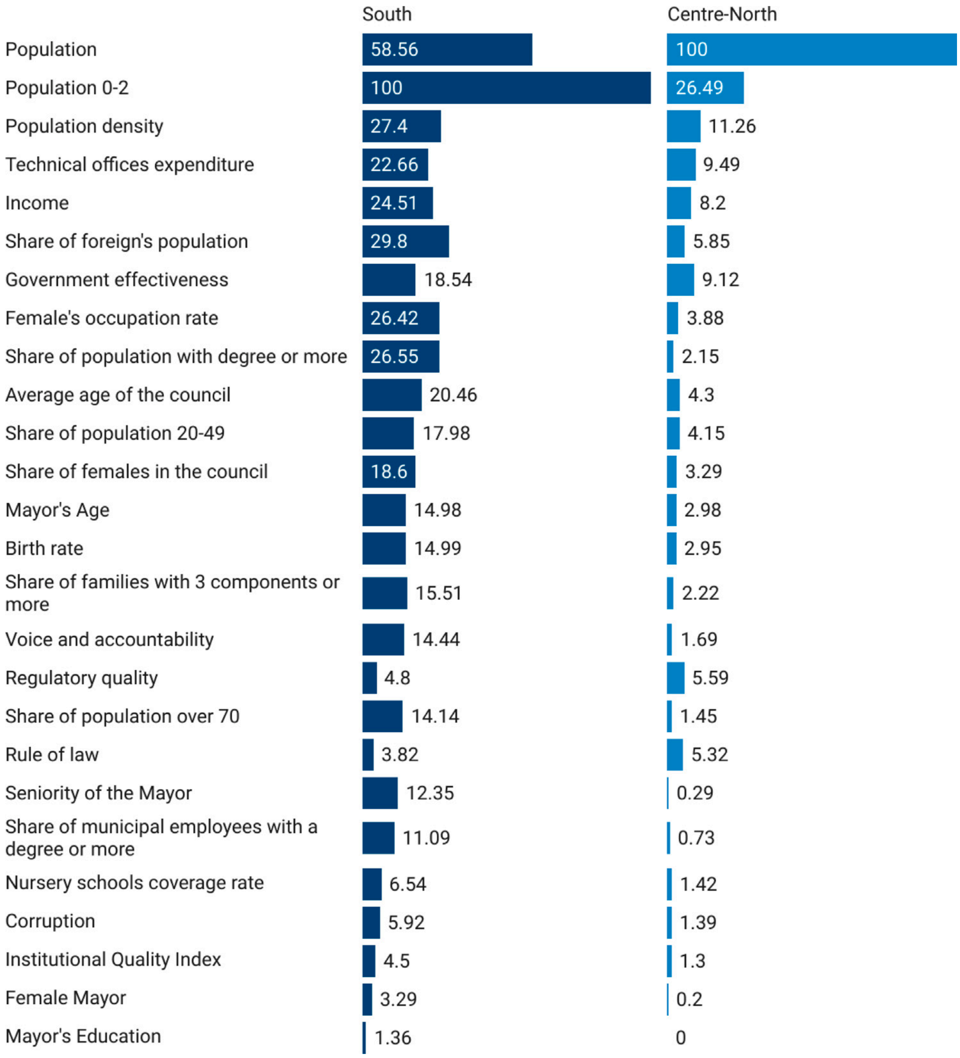


Fig. 3. Feature importance with the best model (Gradient Boosting Machine). GBM model trained on the whole database (bars sorted by average importance between South and Centre-North). At each split in each tree, GBM computes the improvement in the split criterion. GBM then averages the improvement made by each variable across all the trees where the variable is used. The variables with the largest average improvement are considered the most important (Greenwell et al., 2019). Features – with their values scaled to a maximum of 100 – are ranked based on their average importance across both the South and Centre-North. The Figure does not include all variables, as some had an importance score of zero, indicating they did not contribute to the model's predictive power.

fine-tuned through ten repetitions of five-fold cross-validation on the training set.[19] The focus of this section will be on two main aspects: the feature importance and the partial dependence. It is important to emphasize that feature importance (Fig. 3), which indicates the improvement each feature contributes to the prediction task (Greenwell et al., 2019), does not reveal the direction of the relationship between features and local government inertia. To examine the sign and nature of these associations, we use partial dependence plots (PDPs) to visually disentangle this relationship without requiring a predefined mathematical model, allowing us to identify potential non-linearities. In this section, we report PDPs with two input features of interest, able to show the interactions among the two features. For example, the two-variable PDP in Fig. 4 shows the dependence of the probability of not participating in the call on joint values of total population and population 0–2. We can see an interaction between the two features: with low population and low population 0–2 there is a higher probability of not participating in the call (more green to yellow). On the contrary, higher levels of both features are associated with a lower probability of not participating in the call (more purple). Notice that for figures related to Southern and Centre-Northern municipalities, we do not use the same scale colours, as doing so could

[19] Hyperparameters Best Tune are reported in footnote 18. The GBM regression has been implemented in R, using the `gbm` package (Greenwell et al., 2019).

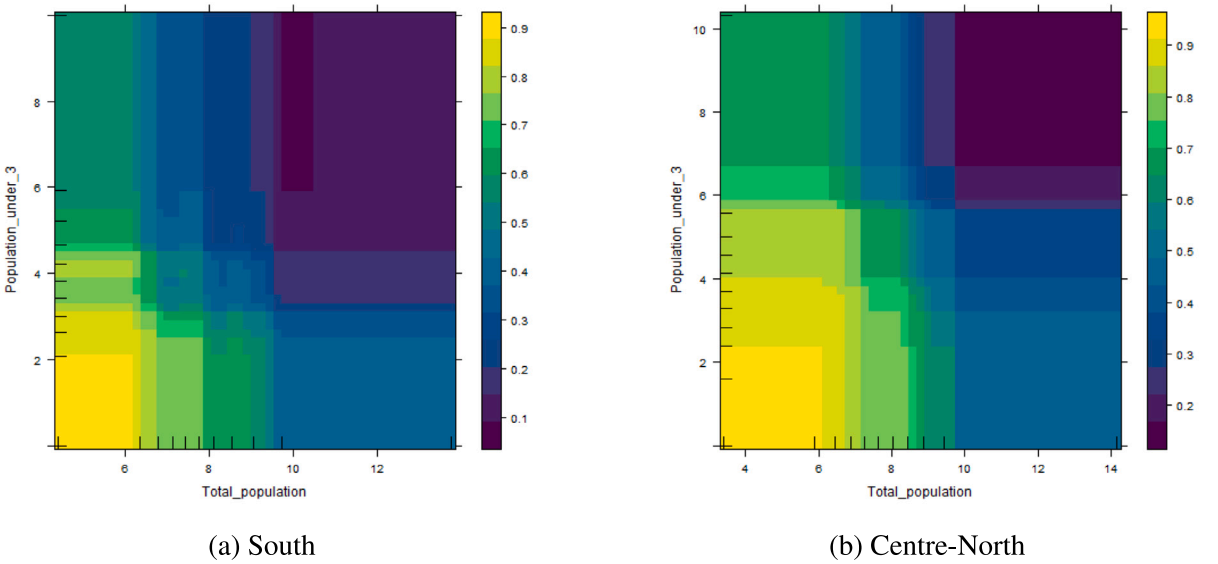


Fig. 4. Partial dependence plots for (log) total population and (log) population 0–2 years. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

obscure some of the nuances in predicted probabilities that are crucial for interpretation. This is due to significant differences across the Southern and Centre-Northern regions in the predicted probability of inertia. In the PDPs analysis, we primarily focus only on the most influential factors explaining local government inertia.[20]

Results of the features' importance are shown in Fig. 3. As observed in the prediction task, there are differences between the Southern and Centre-North areas, as indicated by a Pearson correlation coefficient of 0.609 between the feature importances. The low, yet positive, correlation is expected given the two factors differentiating the samples: the 40 percent funding quota for southern regions and the exclusive reopening of the call in these areas, which create distinct competitive conditions alongside significant regional differences in public sector performance.

The three most important factors are those related to population. In particular, the most important factor in the Centre-North and the second most important factor in the South is the total population, indicating that the size of the municipality plays a significant role in its inertia to compete for cohesion funding calls. The most important factor in Southern municipalities and the second in the Centre-North is the population aged 0–2. On this point, it is possible that many municipalities that have low coverage of childcare services (as we only consider municipalities below 33%) are not particularly interested in obtaining funds to open a nursery because they have very few children under 3 years. Thus, the third most important factor on average is population density (Fig. 3), which is strongly linked to urbanization, an indicator recognized as crucial for the effectiveness of cohesion policies (Albanese et al., 2023). In particular, the predominant role of population size and density in both Southern and Centre-North regions aligns with studies showing the different effects of cohesion policy in urban and rural areas, as highlighted by Gagliardi and Percoco (2017) and Albanese et al. (2021). To highlight the influence of population features on the predicted inertia of local government, Fig. 4 presents the partial dependence plots for the two most significant factors: total population and population under 3 years.[21] They

[20] For population and socioeconomic factors, we focused on the two most relevant variables within each category. For the politics one, we presented the top two factors by importance, i.e., the average age of the council and the share of females in the council; however, we displayed them in separate graphs. Each was paired with what we considered the most relevant factors for joint interpretation: mayoral seniority with average council age, and female mayor with the share of females in the council. The first combination captures an overall political aspect, while the second allows us to explore the role of women in politics. Regarding the demand factors, we present the most important feature, i.e., the share of the foreign population, alongside the birth rate. We selected the birth rate despite its slightly lower importance (2.2% versus 3.44% for the second most important factor, 'female occupation rate') because we believed it to be more relevant for the discussion. For institutional factors, we focus on the two most important features of institutional quality in a strict sense, as indicated by the components of the Institutional Quality Index: government effectiveness and voice and accountability. Finally, we cross-reference the nursery school coverage rate with the expenditure on technical offices and the (log) population of children under three years old, irrespective of their feature groups. The relationship with technical office expenditure highlights our assumption that the capacity of public administrations in project management is crucial for addressing the paradox of increasing demand alongside reduced allocations. Meanwhile, analysing nursery coverage concerning the population under three supports the argument that municipalities with lower coverage rates may be less inclined to seek funding for opening nurseries due to their very small child populations, potentially undermining the policy's goal of stimulating demand.

[21] The PDPs show the log transformation.

are both the main drivers able to predict the probability of not participating in the call. Smaller municipalities are more likely to not participate, regardless of the Population under 3. This may be partially connected to the lack of administrative capacity of smaller local governments, unable to plan in the medium to long term. Notably, the link between the size of the municipality and administrative capacity may not be fully captured by our Institutional Quality Index, as it is measured at the provincial level (Nifo and Vecchione, 2014). The influence of the population aged under 3 closely aligns with the overall population impact. This could be attributed, in part, to the tendency of municipalities with a low number of children to not perceive a demand for nursery services, resulting in fewer applications to the call. It appears logical that factors linked to population matter, as childcare in sparsely populated areas, may inherently face economic challenges. However, this is the very rationale behind public intervention efforts aimed at encouraging a rise in the birth rate. In this regard, the negative impact on participation, stemming from factors like low population density and birth rate, which justify fund allocation, puts municipalities with greater investment requirements at a competitive disadvantage.

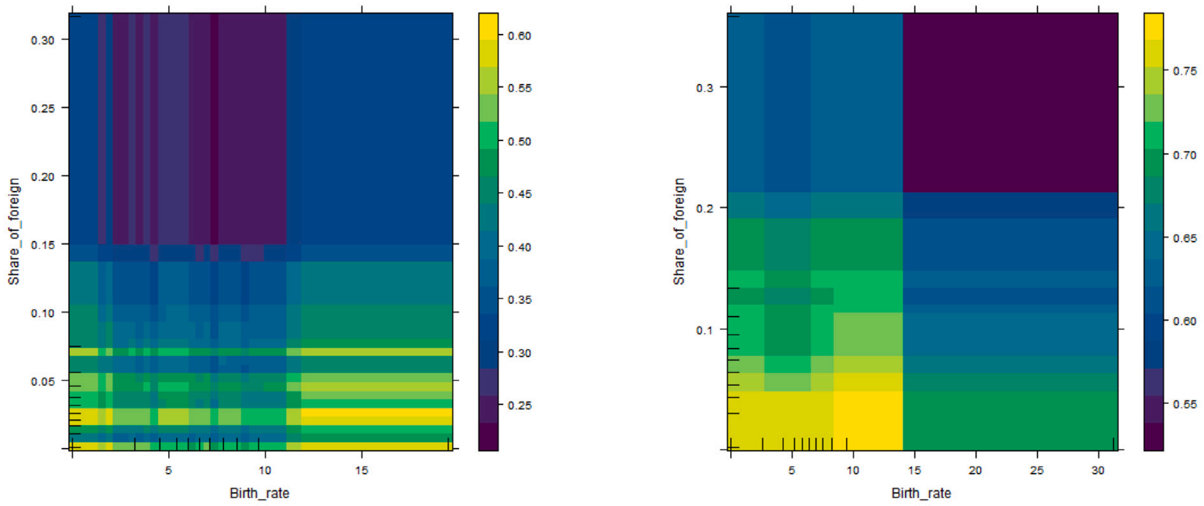
In southern municipalities, the population-related characteristics collectively contribute to approximately 40 percent of total importance, while in centre-northern municipalities, they account for 68 percent of overall importance. This difference may partly stem from the reopening of the call in southern municipalities (see Section 2), allowing other municipal characteristics beyond population to gain prominence. To further assess the impact of population features, we experimented with a model that exclusively incorporates these three features to predict local government inertia. The performance results of this model, presented in Table A.3 and Table A.2 in the Appendix, align closely with the outcomes of the primary model illustrated in Table 3: the best accuracy (EN) is 0.688 (instead of 0.701) in the South and it is 0.751 (instead of 0.755) in the Centre-North. This validation underscores the significance of population factors and highlights the efficacy of machine learning methodologies, especially in contexts where only a limited set of indicators is typically accessible. Conversely, to examine the influence of other variables and potential confounding factors, we performed an exercise that excluded population-related features. The results, shown in Table A.5 and Table A.4, indicate that prediction performance remains good (accuracy significantly higher than the no-information rate), though slightly reduced compared to the full model: best accuracy is 0.664 in South (NN) and 0.741 in Centre-North (RF). This suggests that while population features are key predictors, other factors also contribute meaningfully to the model's performance.

The second most important category of factors explaining the inertia of local governments is related to the demand, i.e., the proportion of the foreign population, who are more likely to use daycare than the non-foreign population because they are less likely to have a family network that can assist the children (Mussino and Ortensi, 2023), the female occupation, the birth rate, the proportion of the population over 70, the cover of nursery schools, the proportion of the population 20–49, and the proportion of families with 3 components or more. Demand factors are around 23 percent and 9 percent of importance for southern and centre-north municipalities, respectively. Fig. 5 shows the partial plots for the most relevant demand factors in Fig. 3: birth rate and the proportion of the foreign population.[22] In both areas, the higher probability of not participating in the call is concentrated in municipalities with a lower birth rate and a lower proportion of the foreign population.[23] It appears that demand primarily influences applications in all municipalities although with some differentiation: in the south municipalities the proportion of foreigners is predominant while in the north the birth rate is more important. This differentiation could be attributed to regional disparities in service availability (see Table 1) and cultural context, which shape demographic pressures and local government responsiveness to social integration policies (Van Wolleghem, 2022). Furthermore, the positive impact of the two demand factors investigated on applications for the call appears to be more pronounced in municipalities in the northern regions; that is, in the right panel of Fig. 5, the upper right quadrant is more purple, and the bottom left quadrant is more yellow compared to the left panel.[24] This difference can be partially explained by an additional funding call exclusively designated for the Mezzogiorno regions (see Section 2). This additional funding created a less competitive environment in the South by ensuring dedicated resources that were not available elsewhere. As a result, local policymakers may have faced reduced pressure to compete aggressively for funds or resources, which likely eased political tensions arising from local demands. Overall, the positive role of demand-related factors raises apprehensions regarding the suitability of allocating cohesion funds to address issues that should ideally be addressed through regular expenditure. This paradoxical relationship between demand and need highlights the complex interplay between childcare availability and demographic trends. As argued by Scherer et al. (2023), childcare services hold the potential to boost fertility by reducing parenting costs and promoting gender equality, which can encourage families to have more children. Empirical findings suggest that while these effects are only partially convergent (Bergsvik et al., 2021; Scherer et al., 2023), they can nonetheless materialize over time, as demonstrated by Rindfuss et al. (2007, 2010), who notes a delayed yet positive impact of expanded childcare on fertility. Similarly, Del Boca (2002) documents a modest increase in birth rates associated with greater childcare availability in Italy, underscoring the context-specific and socio-demographically influenced nature of this relationship. Conversely, when fertility declines, demand for childcare services diminishes, prompting facility closures and further undermining their availability. This creates a self-perpetuating cycle: a lack of nursery schools undermines fertility incentives, while low birth rates reduce incentives to apply for nursery funds. Structural, demographic, and cultural factors add further complexity to these patterns (Vitali and Billari, 2017). Our findings corroborate these dynamics. Municipalities with fewer children may not perceive adequate demand to justify seeking nursery-school funds, thus missing an opportunity to break the cycle and harness childcare provision as a means to reinvigorate local fertility rates.

[22] We selected the birth rate despite its slightly lower importance (2.2 percent versus 3.44 percent for the second most important factor, 'female occupation rate') because it is more relevant for the discussion. The partial dependence plot for female occupation reveals a nonlinear pattern, exhibiting an inverted U shape in southern municipalities and a U shape in northern municipalities.

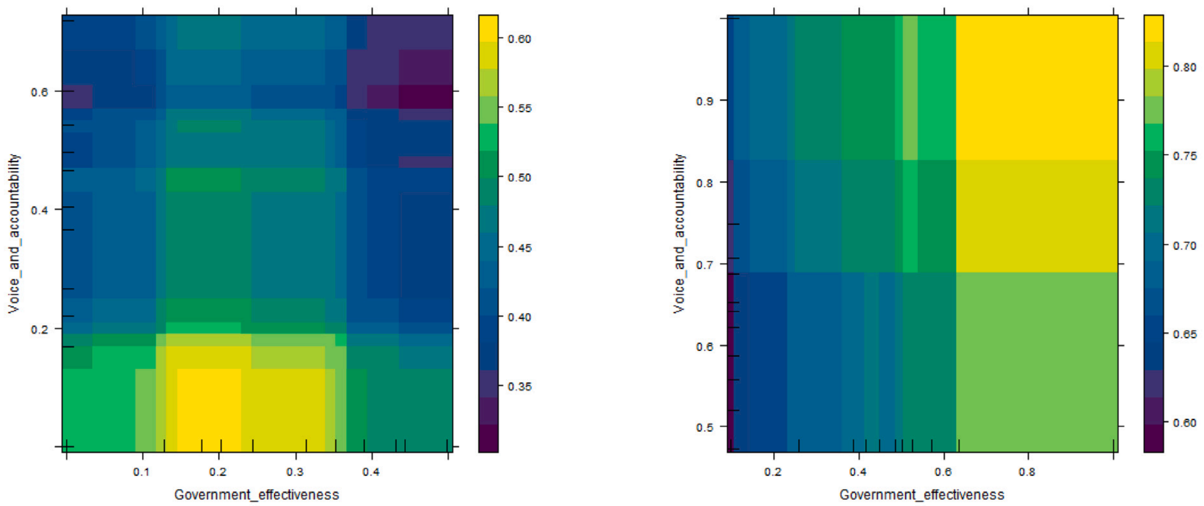
[23] We refer to high and low values within each region.

[24] Although the colours in the two panels represent different scales, the comparison here focuses not on the actual values but on the trend, which appears more linear in the Centre-North municipalities.



(a) South (b) Centre-North

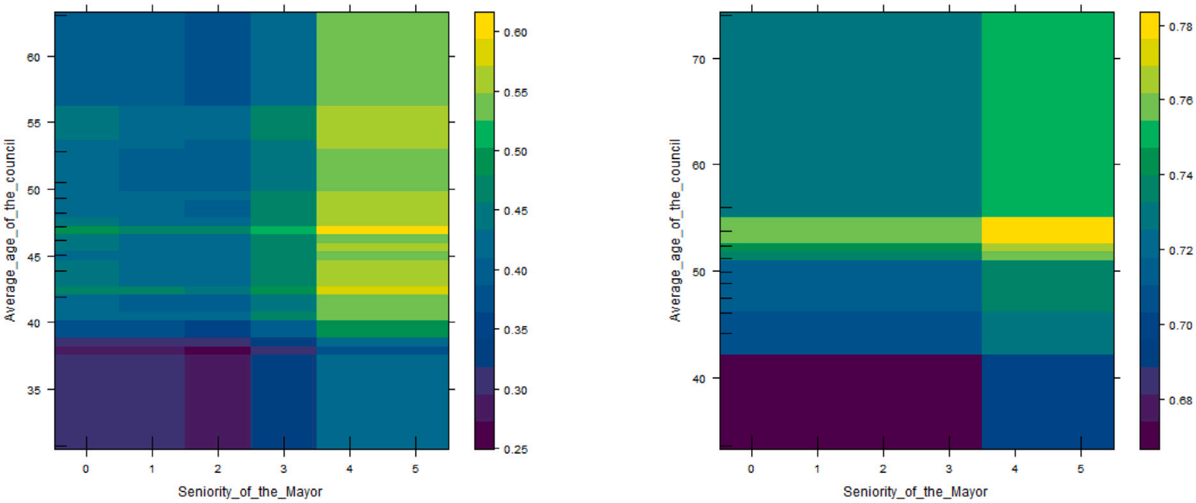
Fig. 5. Partial dependence plots for birth rate and share of foreign population. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).



(a) South (b) Centre-North

Fig. 6. Partial dependence plots for government effectiveness and voice and accountability. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

Other significant factors explaining inertia in both Southern and Centre-Northern municipalities are related to institutional quality, as measured by Nifo and Vecchione (2014), technical office expenditure, and the education level of municipal employees. In particular, the Institutional Quality Index is important as well as all the components of the index (Corruption, Government effectiveness, Regulatory quality, Rule of law, and Voice and accountability). The importance of Institutional quality strongly confirms the idea of Becker et al. (2013) on the role of local institutions in cohesion policy effectiveness. Furthermore, these results align with papers highlighting the role of administrative capacity in explaining the deficiency in EU funds absorption (Incaltarau et al., 2020; Milio, 2007; Surubaru, 2017). In Fig. 6 we show the PDP for the first two Institutional Quality Index components



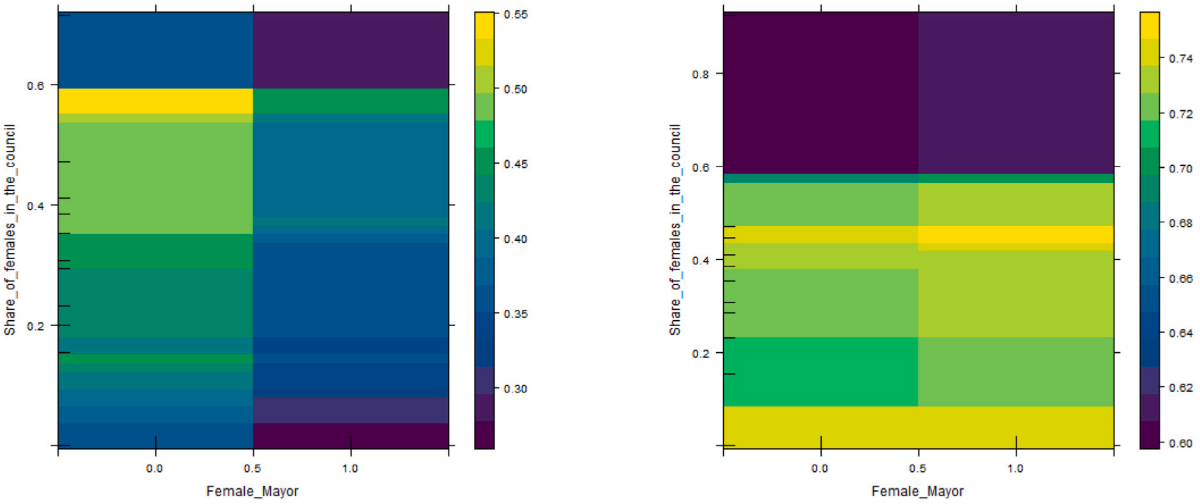
(a) South (b) Centre-North

Fig. 7. Partial dependence plots for seniority of the mayor and average age of the council. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

that are most important in average (Fig. 3): Government Effectiveness and Voice and Accountability. In southern regions, higher Government Effectiveness and higher Voice and Accountability are associated with a lower probability of not participating in the call. This is quite expected and totally in line with the literature highlighting that a lower quality of the local institution seems to be associated with a lower effect of the cohesion policy (Becker et al., 2013). However, this association does not hold in the northern municipalities. This may depend on the fact that the institutional quality is, on average, higher in northern regions (this can be also noted by comparing the axes of the two panels in Fig. 6), and the fact the institutional quality has lower heterogeneity in northern regions. To a certain degree, the beneficial impact of strong local institutions is somewhat diminished when these institutions are already well-established and of high quality. In other words, the correlation between the quality of local institutions and their positive outcomes may not be as pronounced or influential in municipalities where institutions are already functioning at a high standard. An additional explanation for this counterintuitive phenomenon may lie in preference-based factors. Van Wolleghem (2022) examines these factors, particularly the influence of government priorities and societal preferences on fund utilization. In this context, lower prioritization of specific funds in regions with higher institutional quality could drive selective non-participation.

Other notable factors, though with less impact (Fig. 3), include individual characteristics of local policymakers, such as the proportion of females in the council, the Mayor's age, and the average age of council members. Regarding age, Alesina et al. (2019) noted the tendency of younger politicians to behave strategically, increasing spending and obtaining more transfers from higher levels of government, and these factors can somehow affect our outcome variable. Regarding gender, it has been shown that women in politics are usually more concerned about peoples' well-being, show higher cooperation and team working skills, and are less likely to engage in corruption, compared to their male counterparts (Chattopadhyay and Duflo, 2004; Hernández-Nicolás et al., 2018). Consequently, female political participation may affect the policies implemented and the applications to a call that can support gender equality and assist families in balancing their personal and professional lives (Funk and Gathmann, 2015). Moreover, our result on the important role of local policymakers in the cohesion policy aligns with the recent literature that introduced political economy elements into the cohesion debate (Buscemi and Romani, 2022; D'Amico, 2021). Fig. 7 shows the PDP for two of the most important political features: the seniority of the mayor (years in charge)[25] and the average age of the council. Regarding average age, younger politicians (particularly those under 40) are less likely to miss the funding opportunity in both areas. This observation could be attributed, at least in part, to the political aspirations of these politicians, who may exhibit a greater degree of concern for their career trajectory, as demonstrated in Alesina et al. (2019). Another explanation is that younger policymakers may be more attuned to childcare issues, potentially because they have children themselves. Regarding the year in which they are in charge, there are some differences between the two areas. In the southern regions, a sort of U-shaped pattern emerges, indicating that politicians are more inclined to engage in initiatives during the second year of their tenure. This suggests that they refrained from participation

[25] Article 51 of *Testo Unico sull'ordinamento degli enti locali* establishes the term of office for the mayor at five years, mirroring the duration of the municipal council.



(a) South (b) Centre-North

Fig. 8. Partial dependence plots for female mayor and mayor's education (degree or more). GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

at the outset, possibly due to inexperience, and abstained, more significantly, from involvement when they were nearing the end of their term, likely because they anticipated that the investment would not reach completion before the upcoming election. It is worth emphasizing that if politicians apply within their second or third year, the likelihood of achieving results by the end of their mandate remains high, thanks to the clear implementation timelines set by the Next Generation EU deadlines.[26] In northern municipalities, we observe a similar level of inertia as a politician's term lengthens, but there is also a high interest in funding calls at the beginning of their mandate. This pattern may indicate that, while political strategies are similar across both regions, northern politicians might be better prepared or equipped at the start of their careers. This difference in early-term engagement may reflect the impact of social capital on the political selection process. In regions with high social capital, such as in the North, politicians are often chosen based on community trust and civic responsibility, which likely equips them with better preparation and motivation at the start of their terms (Putnam, 1994; Gagliarducci and Nannicini, 2013; Nannicini et al., 2013)

Fig. 8 shows the impact of gender in municipal governance by considering two important characteristics: the gender of the mayor and the percentage of females in the municipal council. It is important to note that, regardless of the measurement method, female presence positively impacts participation in the call across both areas: in both panels, the upper right quadrant displays a stronger purple hue, while the lower left area appears more yellow. This aligns with the literature suggesting that women in politics often show a greater concern for community well-being, particularly through services that support gender equality (Chattopadhyay and Duflo, 2004; Hernández-Nicolás et al., 2018; Funk and Gathmann, 2015). However, the specific feature driving this effect differs between Southern and Central-Northern municipalities. In the South, female mayors have a particularly strong impact, as municipalities led by women show notably higher application rates. In the Central-Northern regions, female representation on the council has an even greater influence, surpassing its effect in the South. This is likely because greater representation of women on a council ensures that their perspectives and experiences are more broadly considered in policy decisions, whereas a single female leader in a predominantly male environment might have limited influence over specific policies.

Furthermore, important factors for predicting inertia in both Southern and Centre-Northern municipalities are directly connected to socioeconomic development such as the level of education and the level of income. Overall, these features' importance confirms what has been shown by the growing body of literature highlighting how human capital development and the quality of local institutions may undermine or enhance the effectiveness of European funds (Becker et al., 2013; Aiello et al., 2019; Rodríguez-Pose and Garcilazo, 2015). Our result corroborates previous findings by showing that these factors influence the inertia of local governments to participate in cohesion calls. Fig. 9 shows the PDPs for the average income and proportion of the population with a degree or higher in the municipality. The effect of the proportion of the population with a degree or higher is quite linearly negative on the inertia of local government both in Southern and Northern municipalities. Municipalities with highly educated people are less likely to lose financing opportunities, mainly in the southern municipalities. The influence of income on the behaviour of local

[26] The deadline for Italy's National Recovery and Resilience Plan was explicitly set to 2026 (Government of Italy, 2021).

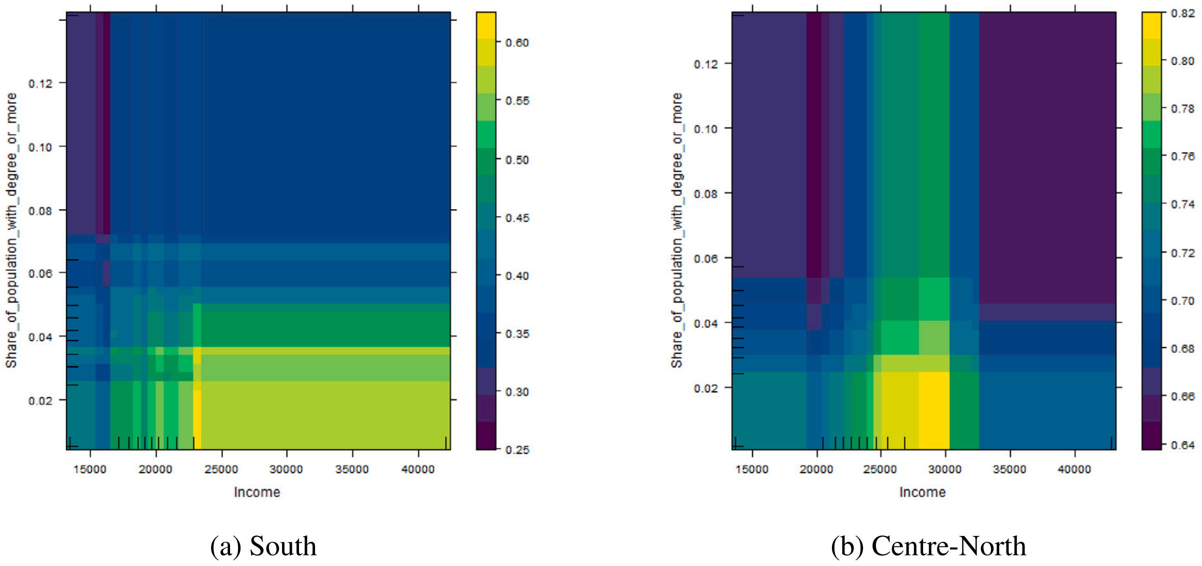
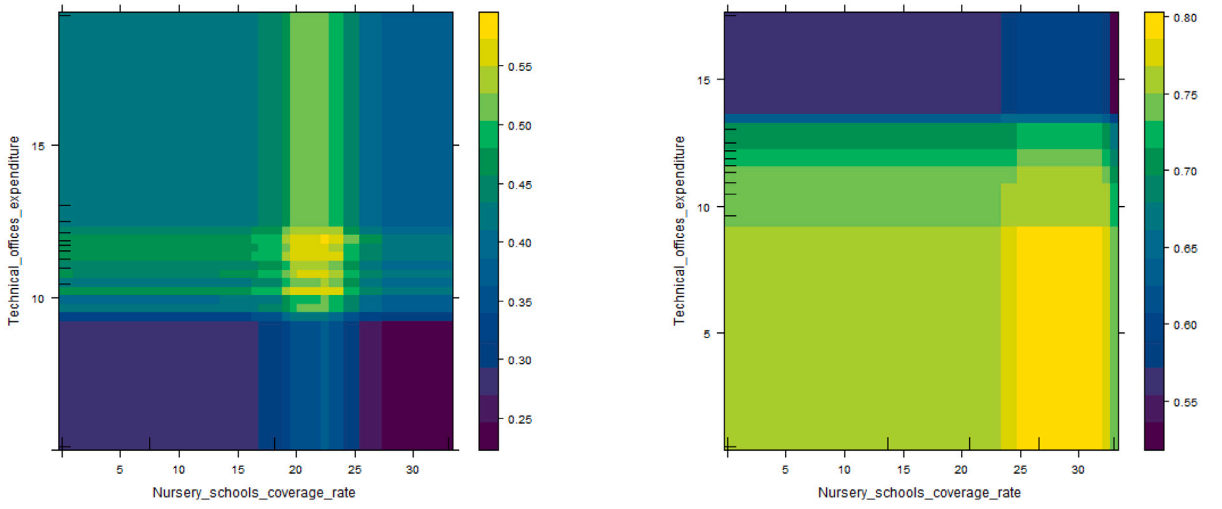


Fig. 9. Partial dependence plots for income and share of population with a degree or more. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

governments exhibits a distinctive pattern, and this pattern varies significantly between the Centre-North and South regions. Rather than following a straightforward linear relationship, the impact of income on the inertia of local government takes on a quite positive direction in the South and a curvilinear shape, resembling an inverted U in the North. Multiple factors may contribute to these findings. Although income level often serves as a proxy for development, higher-income individuals generally utilize childcare services more frequently. However, this reliance tends to be on private rather than public services, given that their financial flexibility reduces the need for subsidized childcare. This is supported by OECD data, which shows that high-income families are significantly more likely to use childcare services overall, whereas lower-income families, often constrained by cost, depend more on accessible public options (Adema et al., 2016). These patterns suggest that the relationship between income and demand for public childcare services may be non-linear, with demand not consistently increasing as income rises but instead varying at different income levels. This complexity underscores the importance of using advanced, non-linear models in policy analysis to capture these nuanced dynamics.

In Fig. 10 we show the PDP for the log transformation of the Technical office expenditure and the Coverage of nursery schools.[27] We present these results because technical office expenditure ranks as the fourth most important factor on average (Fig. 3), directly tied to the budget of the office responsible for project development. The nursery school coverage rate serves as a direct measure of need (i.e., the lower the coverage, the greater the need). These plots indicate that, in the Centre-North of Italy, there is a negative correlation between expenditure on technical offices and the inertia of local administrations. Conversely, in southern municipalities, inertia does not appear to be a resource issue: high spending on technical offices does not translate into improved efficiency. This territorial differentiation could stem from the structural differences in how the call was implemented across the country. In the North, a single call likely fostered greater competition among municipalities, which could have enabled better-equipped local governments to prepare projects more quickly (Cunico et al., 2024). In the South, where the call was reopened, municipalities had more time to prepare, potentially reducing the importance of technical office resources. This is further supported by the varying importance of technical office expenditures in the two regions, accounting for 23 percent of the influence in the North and 11 percent in the South. An additional factor is public sector efficiency, particularly at the municipal level, which is higher in northern municipalities. Consequently, public expenditure has a more pronounced effect on local government responsiveness in the North (Agasisti and Porcelli, 2023). Paradoxically, in southern municipalities, we observe a slightly lower reluctance to respond to the call in areas with greater nursery school coverage. This trend contrasts with northern municipalities, where higher nursery coverage is associated with a greater probability of non-application. It is important to note that the analysis focuses on municipalities with coverage rates below 33%, primarily comparing very low to moderately low coverage levels.

[27] We use the total value of technical office expenditure but we observe the same results on per capita expenditure for technical office. Results are available upon request.



(a) South (b) Centre-North

Fig. 10. Partial dependence plots for coverage of nursery schools and (log) technical office expenditure. GBM model trained on the whole database. The partial dependence plots are developed in R by the `pdp` package (Brandon, 2017).

5. Conclusions

This paper explores the predictability of local governments that are likely to miss out on funding opportunities despite their needs. In this regard, open calls within the Italian National Recovery and Resilience Plan, financed by the European Next Generation EU funds, are used as a case study. By leveraging machine learning techniques, the study sheds light on the determinants of inertia among potential beneficiaries, particularly focusing on the allocation of funds for childcare services.

The findings demonstrate a robust capacity to accurately predict, out-of-sample, which local government entities are less likely to participate in funding initiatives. Notably, these predictions remain reliable even when using only a minimal subset of readily available features (e.g., population-related data) and disregarding territorial call differentiations, thereby underscoring the strong predictive power of flexible machine learning techniques in heterogeneous contexts. Furthermore, the analysis identifies key economic, institutional, and political factors that shape local government inertia, with critical implications for the effectiveness of cohesion policies.

The empirical findings reveal that population-related factors, such as total population size and density, dominate non-participation predictions. Smaller and more rural municipalities, often the most disadvantaged, are systematically less likely to pursue funding opportunities. This creates a paradox: the regions most in need of infrastructure investment are the least likely to secure funding, thereby deepening regional inequalities instead of reducing them. Demand-related factors, such as birth rates and the proportion of foreign residents, further highlight this paradox. While municipalities with higher demand are more likely to apply for funding, those with lower birth rates and minimal service coverage enter a self-reinforcing cycle of low demand and non-participation, undermining the policy's goal of reducing disparities. Institutional quality also plays a relevant role. Municipalities with stronger governance indicators, higher administrative capacity, and better institutional frameworks are more likely to apply for funding, while weaker institutions in underdeveloped areas limit their capacity to engage effectively. These findings align with existing literature, emphasizing the critical role of strengthening local administrative capacities and governance to foster local development. The study highlights the influence of political factors. Characteristics such as the age, seniority, and gender of mayors and council members emerge as important predictors of participation. Younger mayors and councils tend to demonstrate greater engagement, possibly driven by their career ambitions or closer alignment with the policy priorities, such as childcare and gender equality. Female representation in municipal leadership is also associated with higher participation rates, suggesting that gender diversity in politics can positively influence funding applications, particularly for initiatives aimed at supporting families and promoting inclusivity. The seniority of mayors displays a U-shaped relationship with participation. Participation is most likely during the middle years of a mayor's term, reflecting a strategic effort to align investment outcomes with electoral timelines. Certain factors affect call participation differently across southern and central-northern municipalities. This discrepancy underscores the importance of considering each region's unique circumstances, paving the way for more targeted and effective policy interventions.

These findings extend beyond Italy, emphasizing universal challenges in funding utilization tied to administrative capacity and institutional quality. Research on EU Cohesion Policy highlights the critical role of governance and administrative capacity in fund absorption, with weaker regions often struggling to meet application requirements (Van Wolleghem, 2022; Cunico et al., 2024; Mendez and Bachtler, 2024). Notably, such challenges are not exclusive to the EU or Cohesion Policy. In the U.S., studies similarly reveal that the administrative capacity of subnational governments is vital for accessing and effectively utilizing intergovernmental grants (Carley et al., 2015; Nicholson-Crotty, 2015). Our findings add to this discussion by demonstrating that machine learning can predict which local governments are likely to miss financing opportunities, even when resources are critically needed. By identifying key factors influencing non-application rates, this approach provides policymakers with actionable insights for targeted interventions to address administrative inertia and enhance fund absorption. In this context, centralized management of cohesion policies, combined with predictive tools like ours, offers a promising solution for countries with significant regional disparities in administrative capacity. Centralization can streamline processes, reduce administrative barriers, and ensure consistent implementation across diverse regions (Mendez and Bachtler, 2024). Together with capacity-building efforts, this strategy can enhance equity and efficiency in fund allocation globally, offering a replicable framework to address disparities and maximize the developmental impact of public policies (Bachtrögler et al., 2019).

5.1. Practical implications and future research

This analysis provides insights for policymakers and practitioners, shedding new light on the dynamics that lead to the under-utilization of available funding. Identifying in advance potential non-participants in calls can serve as a valuable tool for policymakers to push towards the policy target, and effectively allocate resources within the framework of the policies. In particular, the model can serve as an early warning system by flagging areas or groups that are at higher risk of missing funding opportunities. This allows funding agencies to proactively reach out, provide additional support, or modify the application process to make it more accessible. In the existing policy framework, these predictions can be employed to target direct assistance, aiding the local government in promptly formulating appropriate plans, programs, and projects.

Building on the predictive insights, policymakers could implement targeted capacity-building measures for municipalities with limited administrative resources, particularly those aimed at enhancing technical skills. The persistence of underdevelopment in certain regions is closely tied to the quality of local institutions, highlighting the need for policies capable of succeeding despite inefficiencies in local governance. Additionally, predictions can be used to develop tailored incentives that encourage municipalities to apply for funding and to design communication strategies adapted to their specific needs. The predictive outputs could also inform the customization of funding calls, ensuring they address the distinct requirements of targeted areas. Recognizing the factors that drive the likelihood of missed funding offers valuable guidance for refining and optimizing eligibility criteria in future funding opportunities, thereby ensuring closer alignment with the needs of intended recipients.

Adopting machine learning to predict funding allocation challenges opens promising avenues for research and policy development in public programs and spending. Future research could build on this approach by incorporating more advanced analytics, leveraging the ongoing increase in computational power. Moreover, more robust monitoring processes could significantly enhance model performance and, in turn, help reduce participation barriers. From a methodological standpoint, the machine learning framework introduced in this study could be adapted to contexts beyond cohesion policy, particularly where optimal fund allocation is crucial. This approach could include exploring alternative data sources, which have become increasingly available due to the proliferation of internet-based platforms and Big Data, as machine learning techniques excel at managing complex datasets. Multiple avenues remain open for further investigation regarding the insights into the importance of features highlighted in this study. First, longitudinal studies could assess whether targeted interventions, such as training programs, lead to sustained participation and fund absorption improvements. Second, cross-country comparative analyses could provide deeper insights into how institutional and socio-economic contexts influence the effectiveness of cohesion policies in different regions. Third, exploring the role of political dynamics, such as the alignment of local electoral incentives with policy design, could further clarify the interplay between governance and funding outcomes.

Declaration of competing interest

We have no conflict of interest to declare.

Appendix

See Tables A.1–A.5.

Data availability

Data will be made available on request.

Table A.1
Data source.

Variable	Year	Source
Call partecipation	2020	Ministry of Education and Excellence
	2021	PNRR Istruzione
Population	2019	Istat
Population 0–2	2021	Istat
Population density	2020	Istat
Income	2020	Ministry of Economy and Finance
Share of population with degree or more	2019	Istat
Share of foreign's population	2019	Istat
Share of population 20–49	2019	Istat
Share of population over 70	2019	Istat
Birth rate	2019	Istat
Female's occupation rate	2019	Istat
Share of families with 3 components or more	2020	Istat
Nursery schools coverage rate	2020	Istat
Share of municipal employees with a degree or more	2020	Ministry of Economy and Finance
Technical offices expenditure	2021	openpolis processing on openBDAP data
Institutional Quality Index	2019	Nifo and Vecchione (2014)
Corruption	2019	Nifo and Vecchione (2014)
Government effectiveness	2019	Nifo and Vecchione (2014)
Regulatory quality	2019	Nifo and Vecchione (2014)
Rule of law	2019	Nifo and Vecchione (2014)
Voice and accountability	2019	Nifo and Vecchione (2014)
Average age of the council	2020–2021	Ministry of the Interior
Share of females in the council	2020–2021	Ministry of the Interior
Average age of assessors	2020–2021	Ministry of the Interior
Share of females among assessors	2020–2021	Ministry of the Interior
Mayor's Age	2020–2021	Ministry of the Interior
Mayor's Education	2020–2021	Ministry of the Interior
Female Mayor	2020–2021	Ministry of the Interior
Seniority of the Mayor	2020–2021	Ministry of the Interior
Political Party	2020–2021	Ministry of the Interior

The Nifo and Vecchione (2014)'s index originated at the provincial level but finds application at the municipal level.

Table A.2
Results of DeLong's test for ROC curves using only total population, population 0–2, and population density as features.

	South		Centre-North	
	Z	*p*-value	Z	*p*-value
GBM vs. RF	2.357	0.079	3.278	0.019
GBM vs. EN	0.815	0.456	0.33	0.427
GBM vs. NN	0.301	0.634	−0.144	0.499
GBM vs. Logit	1.328	0.255	0.63	0.417

Averages calculated across the repetitions for 10 different random splittings.

Table A.3
Models' performances using only total population, population 0–2, and population density as features.

	South					Centre-North				
	GBM	RF	EN	NN	Logit	GBM	RF	EN	NN	Logit
Accuracy	0.680	0.658	0.688	0.659	0.659	0.750	0.721	0.751	0.739	0.744
Kappa	0.347	0.306	0.362	0.331	0.329	0.339	0.297	0.332	0.245	0.276
AccuracyLower	0.635	0.613	0.643	0.614	0.613	0.719	0.689	0.720	0.708	0.713
AccuracyUpper	0.723	0.702	0.730	0.703	0.703	0.779	0.751	0.780	0.769	0.773
AccuracyNull	0.547	0.547	0.547	0.547	0.547	0.692	0.692	0.692	0.692	0.692
AccuracyPValue	0.000	0.002	0.000	0.014	0.003	0.001	0.073	0.001	0.008	0.002
McnemarPValue	0.099	0.386	0.167	0.000	0.000	0.000	0.002	0.000	0.000	0.000
Sensitivity	0.575	0.590	0.592	0.775	0.772	0.910	0.853	0.920	0.964	0.953
Specificity	0.768	0.715	0.766	0.565	0.566	0.390	0.424	0.372	0.235	0.276
Pos Pred Value	0.673	0.632	0.678	0.596	0.596	0.770	0.769	0.767	0.739	0.747
Neg Pred Value	0.685	0.678	0.695	0.751	0.749	0.660	0.562	0.676	0.747	0.723
Precision	0.673	0.632	0.678	0.596	0.596	0.770	0.769	0.767	0.739	0.747
Recall	0.575	0.590	0.592	0.775	0.772	0.910	0.853	0.920	0.964	0.953
F1	0.619	0.610	0.631	0.673	0.672	0.834	0.809	0.836	0.837	0.838
Prevalence	0.453	0.453	0.453	0.453	0.453	0.692	0.692	0.692	0.692	0.692
Detection rate	0.260	0.267	0.269	0.351	0.350	0.630	0.591	0.636	0.667	0.660
Detection prevalence	0.387	0.424	0.396	0.590	0.587	0.818	0.768	0.830	0.903	0.883
Balanced accuracy	0.671	0.652	0.679	0.670	0.669	0.650	0.639	0.646	0.600	0.614

Figures are estimated on the confusion matrix, which shows a cross-tabulation of the observed and predicted classes, generating the predicted classes based on the typical 50 percent cutoff for the probabilities (Kuhn, 2021). Averages were calculated across the repetitions for 10 different random splittings.

Table A.4
Results of DeLong's test for ROC curves without using total population, population 0–2, and population density as features.

	South		Centre-North	
	Z	*p*-value	Z	*p*-value
GBM vs. RF	0.459	0.526	−0.1558	0.578
GBM vs. EN	0.231	0.557	0.4209	0.437
GBM vs. NN	3.835	0.001	4.132	0.002
GBM vs. Logit	0.200	0.571	0.405	0.446

Averages calculated across the repetitions for 10 different random splittings.

Table A.5
Models' performances without using total population, population 0–2, and population density as features.

	South					Centre-North				
	GBM	RF	EN	NN	Logit	GBM	RF	EN	NN	Logit
Accuracy	0.664	0.666	0.596	0.668	0.667	0.741	0.747	0.712	0.734	0.733
Kappa	0.316	0.317	0.184	0.329	0.326	0.307	0.314	0.219	0.272	0.274
AccuracyLower	0.618	0.620	0.549	0.623	0.621	0.710	0.716	0.680	0.702	0.702
AccuracyUpper	0.707	0.709	0.641	0.712	0.710	0.771	0.776	0.743	0.763	0.763
AccuracyNull	0.546	0.546	0.546	0.546	0.546	0.693	0.693	0.693	0.693	0.693
AccuracyPValue	0.001	0.000	0.107	0.000	0.000	0.006	0.001	0.201	0.011	0.013
McnemarPValue	0.282	0.129	0.002	0.555	0.495	0.000	0.000	0.156	0.000	0.000
Sensitivity	0.578	0.570	0.513	0.618	0.616	0.910	0.923	0.884	0.919	0.917
Specificity	0.735	0.745	0.673	0.710	0.709	0.360	0.350	0.318	0.316	0.320
Pos Pred Value	0.645	0.650	NA	0.639	0.638	0.763	0.763	0.751	0.752	0.753
Neg Pred Value	0.677	0.675	0.641	0.691	0.690	0.639	0.668	NA	0.633	0.630
Precision	0.645	0.650	NA	0.639	0.638	0.763	0.763	0.751	0.752	0.753
Recall	0.578	0.570	0.513	0.618	0.616	0.910	0.923	0.884	0.919	0.917
F1	0.609	0.607	NA	0.628	0.626	0.830	0.835	0.809	0.827	0.827
Prevalence	0.454	0.454	0.454	0.454	0.454	0.693	0.693	0.693	0.693	0.693
Detection rate	0.263	0.259	0.230	0.281	0.280	0.631	0.640	0.614	0.637	0.636
Detection prevalence	0.407	0.398	0.411	0.439	0.439	0.827	0.839	0.821	0.847	0.844
Balanced accuracy	0.657	0.657	0.593	0.664	0.663	0.635	0.637	0.601	0.617	0.618

Figures are estimated on the confusion matrix, which shows a cross-tabulation of the observed and predicted classes, generating the predicted classes based on the typical 50 percent cutoff for the probabilities (Kuhn, 2021). Averages were calculated across the repetitions for 10 different random splittings.

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