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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 competitive funding opportunities within cohesion policies, utilizing machine learning and analyzing 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 that are likely to abstain from invitations, also identifying key determinants. Population-related factors play a pivotal role in predicting inertia, alongside other service-demand-related elements, particularly in regions with limited services. The study emphasizes the importance of local institutional quality and individual attributes of policymakers. The adverse effects on participation resulting from factors that justify fund allocation may place regions with higher investment needs at a competitive disadvantage. Anticipating potential non-participants in calls can aid in achieving policy targets and optimizing the allocation of funds across various local governments.

Keywords: Competitive funding; Cohesion policies; Predictive modeling; Machine learning.

JEL Classification: H5; H7; I3; J1; R5.

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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 (Farole, Rodríguez-Pose, & Storper, 2011; Krugman, 1991). Within this context, there is a notable emphasis on place-based policies directed towards underdeveloped areas (Neumark & 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 remains elusive, given the divergence in outcomes when considering different timeframes, territorial levels, and the utilization of various econometric methodologies (Becker, Egger, & Von Ehrlich, 2018; Mohl & Hagen, 2010). 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 Fang (2017) illustrates that, overall, cohesion funds exhibit a generally positive and statistically significant impact on economic growth. Nevertheless, this impact tends to be relatively modest, particularly when evaluated in relation to the resources allocated. Focusing on the Italian case, in which such policies have been implemented since the post-World War II era, evaluation analyses yield scant empirical support for the notion that they can foster growth in the designated areas (Barone & 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 & 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 (Andini & 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. Referring to government quality indicators, it has been shown that institutional quality shows a wide heterogeneity among regions (Charron, Dijkstra, & Lapuente, 2014). Given that a substantial portion of cohesion initiatives are managed at the local government level, the quality of these local government institutions becomes of pivotal importance. To exemplify this, Becker, Egger, and Von Ehrlich (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, Pascariu, & Surubaru, 2020; Milio, 2007; Surubaru, 2017). Furthermore, local politicians wield a great influence in molding the distribution of financial resources. They can attract public funds even by selecting bureaucrats responsible for managing the allocation process as shown by Buscemi and Romani (2022) with the Italian example of the *Cassa per il Mezzogiorno*. It has been also shown that many institutions currently responsible for administering cohesion funds, particularly local governments, lack the motivation to use these funds effectively (D’Amico, 2021). The argument posits that for cohesion funds to stimulate growth, they should actively transform the local economy, including bringing back talented individuals who have migrated elsewhere. However, those who have left

no longer have a say in local elections, leading local governors to focus on representing the interests of the remaining residents. This bias toward the current population encourages investments that maintain the status quo and bolster declining sectors rather than fostering innovation and development (D'Amico, 2021).

In the literature referenced above, an aspect that has yet to be explored is the potential resistance of local potential beneficiaries to engage in competitive funding opportunities, which is typically how funds are allocated. In practice, since many cohesion funds are distributed through open calls, if the local government, organizations, enterprises, or citizens choose not to participate in such calls, this leads to their exclusion from the competition, subsequently resulting in a missed opportunity to secure funding and advance their development initiatives. Within the EU cohesion policy framework, this is one of the reasons why several governments encountered difficulties in spending their allocated structural funds (European Parliament, 2011). Such suboptimal execution performance has been partially attributed to factors associated with administrative capacity, as discussed by Cunico, Aivazidou, and Mollona (2022). 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 data indicates that regional policies frequently fall short in delivering results in the most underprivileged areas owing to their comparatively restricted planning capacities (Crescenzi & Giua, 2016; Kline & Moretti, 2014; Neumark & Simpson, 2015). If the goal of European 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 thanks to the use of European Next Generation EU funds.¹ We use a machine learning (ML) model to predict local governments that fail to seize funding opportunities, even when such funding is needed, with a specific focus on the allocation of funds for childcare services within the Italian NRRP. 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 non-participants in the calls can serve as a valuable tool for policymakers to push towards the policy target, and effectively allocate resources within the framework of the policy.

Among the scheduled initiatives, the NPRR 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 NPRR funding designated for nursery schools has been structured using specific calls for proposals "*Bandi asili nido*". These calls

¹https://next-generation-eu.europa.eu/index_en; <https://www.italiadomani.gov.it/content/sogei-ng/it/en/home.html>

define the criteria for distributing resources to municipalities in a competitive manner, 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 a pivotal 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 (Baker, Gruber, & Milligan, 2008; Carta & Rizzica, 2018; Cascio, 2009; Fitzpatrick, 2010; Goux & Maurin, 2010; Havnes & Mogstad, 2011; Lefebvre & Merrigan, 2008; Nollenberger & Rodríguez-Planas, 2015). 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 European Council 15-16 March 2022. Presidency conclusions 2002*). However, the majority of municipalities fall significantly short of achieving this level of coverage. Among these, over 3,400 municipalities with a serious shortage of nursery schools (coverage rate below 11 percent) did not participate in the *”Bandi asili nido”* calls (UPB - Parliamentary Budget Office, 2022). 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 are the main determinants of this inertia.

From an empirical perspective, we follow the recent economic literature arguing that targeting policy problems, such as predicting local governments that will miss out on funding chances, does not require ex-post correlation or causal inference solutions, but that new developments in the field of ML are of more use (Einav & Levin, 2014; Kleinberg, Ludwig, Mullainathan, & Obermeyer, 2015). ML techniques are gaining momentum for solving problems connected to poverty targeting (Jean et al., 2016) and the effectiveness of public programs and spending (Andini, Ciani, de Blasio, D’Ignazio, & Salvestrini, 2018). Focusing on the Italian context, recent works have leveraged the potential of ML to predict the bankruptcy of local governments (Antulov-Fantulin, Lagravinese, & Resce, 2021), vaccine hesitancy in municipalities (Carri-eri, Lagravinese, & Resce, 2021), to estimate local mortality and local inequality during the COVID-19 pandemic (Cerqua, Di Stefano, Letta, & Miccoli, 2021; Cerqua & Letta, 2022), and to predict Geographical Indications areas (Resce & Vaquero-Piñeiro, 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, education, 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 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 latter concerns the planning of the inclusion and cohesion mission.² Moreover, it planned to integrate Cohesion Policies with NRPP by ensuring that at least 40 percent of the resources are allocated to the Southern regions (Italian *Mezzogiorno*), the so-called "quota-sud".³ Nevertheless, interventions were not planned based on a territorial mapping of investment needs and NRPP 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.

One of the important investments in the NRPP concerned resources provided for nursery schools and early childhood education and care services, the so-called *Bandi asili nido*. Research indicates that maternal labor supply measures boost mothers' engagement in the workforce and reduce the reservation wage for the unemployed, thereby enhancing their chances of securing employment (Carta & Rizzica, 2018). Promoting the quality and ample accessibility of childhood infrastructure contributes to increased female participation, thereby diminishing gender disparities in the labor market and fostering the accumulation of human capital for sustained long-term growth. This gained prominence as a significant policy consideration at the European level during the meeting of the European Council in Barcelona. The council emphasized the need for Member States to eliminate obstacles to female labor force participation and aim to offer childcare services to a minimum of 90 percent of children aged 3 to mandatory school age, as well as at least 33 percent of children under 3 years old, by the year 2010. Then, after the Covid-19 emergency, both objectives were updated.⁴

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. In fact, Italy shows significant territorial inequalities in the availability and quality of childcare services, as depicted in Figure 1a 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. In particular, the national mean of municipal LEP is around 16 nursery places for 100 children aged 0-2, while in the southern area it is around 9 and in the rest of Italy around 19.⁵ Variations exist among regions, with none, on the average of municipal LEP, meeting the 33 percent threshold. Additionally, when examining provinces (NUTS3

²NRPP 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.

³Southern Italy, also known as *Meridione* or *Mezzogiorno* comprises the administrative regions that correspond to Abruzzo, Apulia, Basilicata, Calabria, Campania, Molise, Sicily, and Sardinia.

⁴A 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.

⁵If 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 LEP) depends on the fact that many (small) municipalities have small or zero LEP.

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.⁶

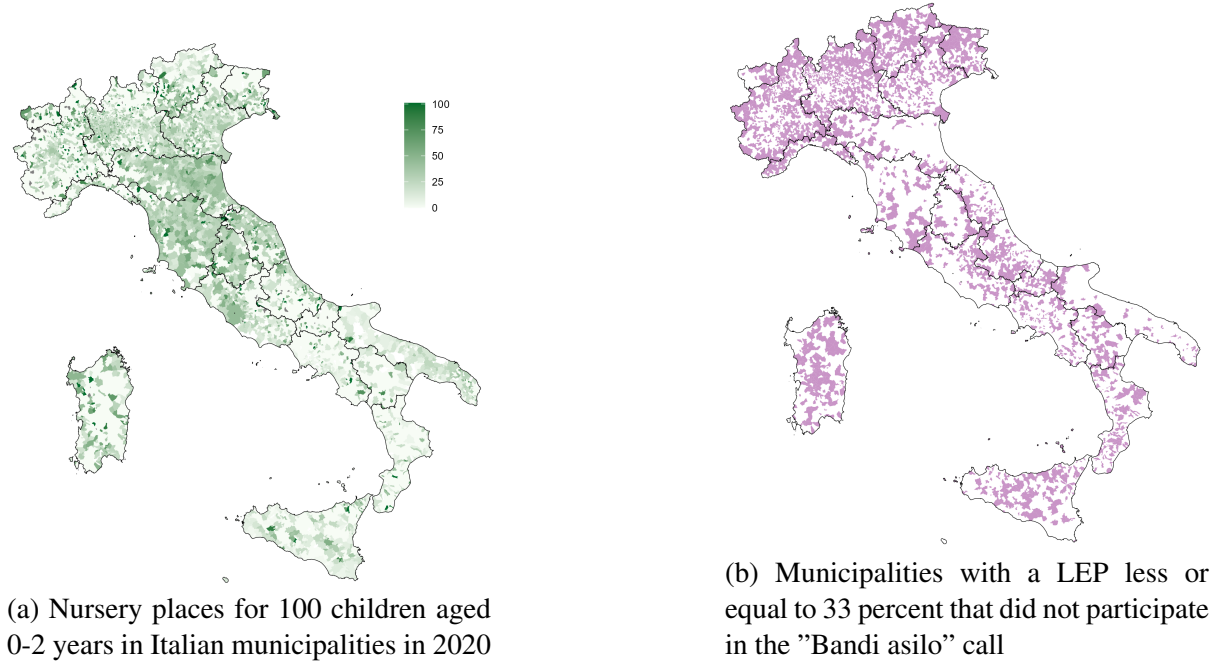
In this framework, the NRRP resources are a unique opportunity to fill territorial gaps. Through Investment 1.1 (Plan for nurseries and nursery schools and early childhood education and care services) of Component 1 (Strengthening the offer of education services: from nurseries to universities) of Mission 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,⁷ was initiated through a public notice on December 2, 2021 (protocol number 48047) by the Ministry of Education. Both the DPCM on December 30 and the public notice on December 2021 provide for access through special calls for proposals open to all Italian municipalities, individually or associated with other municipalities. To address economic and social imbalances, the former 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, financed with NRRP resources, envisaged two constraints: the previously mentioned "*quota-sud*" and considering 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 aims to favour and protect the autonomy of municipalities through competitive calls for proposals and to integrate, in a second stage, the allocation one, in which criteria exist to guarantee the NPRR goals. However, it did not seem to work because around 60 percent of municipalities with a LEP less than or equal to 33 percent did not participate in the calls for proposals. Figure 1b, shows the municipalities with a LEP less than or equal to 33 percent which did not participate in either of the two calls for proposals.

⁶If 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 LEP more than 33 places for children aged 0-2.

⁷2.4 billion for nursery schools, i.e., 0-2 years and 0.6 for schools of childhood, i.e., 3-6 years

Figure 1: Territorial distribution of nursery places and target municipalities



3 Data and Methods

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 includes 2274 municipalities while the latter includes 4191. There are two primary issues that affected this decision: firstly, the NPRR imposes an allocation constraint known as the abovementioned "*quota-sud*" which mandates that 40 percent of the funding must be directed toward the southern regions; secondly, the reopening of the "*Bandi asili nido*" call exclusively for southern regions (see section 2). 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 affect non-application to the call and, consequently the inertia of local government: structural (St), socioeconomic (SE), demand (D), institutions (IQ), and politics (Pol). All features are taken in the period before the call opening. In Table A1 in the Appendix, we show the source of data and the year of reference.

The structural features include population size, population 0-2, population density, and technical office expenses, three dimensions that synthesize the structure, the dynamics, and the capacity or likely difficulty of public administrations of project management. The socioeconomic features consist of income and the proportion of the population with a degree as drivers of the development of territories but also strictly correlated to the demand features of territories. 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. These factors have a dual role because they could drive call participation given that they identify the territories' need to meet an already existing demand on one hand, or the possibility of placing confidence in a particular territory and boosting its demand on the other hand. The institutional features that can be connected to local government inertia in leveraging funding opportunities include the proportion of municipal employees with a degree or more and the provincial institutional quality index (Nifo & Vecchione, 2014) with its five components, i.e., Regulatory quality, Government Effectiveness, Rule of law, Corruption, Voice and accountability. 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.

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

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 $\{St, SE, D, IQ, Pol\}_{i,t-1}$, find the function $f(\cdot)$ (machine learning model) that predicts non-application to at least one call *Bandi asilo* ($NoApp_{i,t}$):

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

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 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 & 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, Venables, & Ripley, 2016).

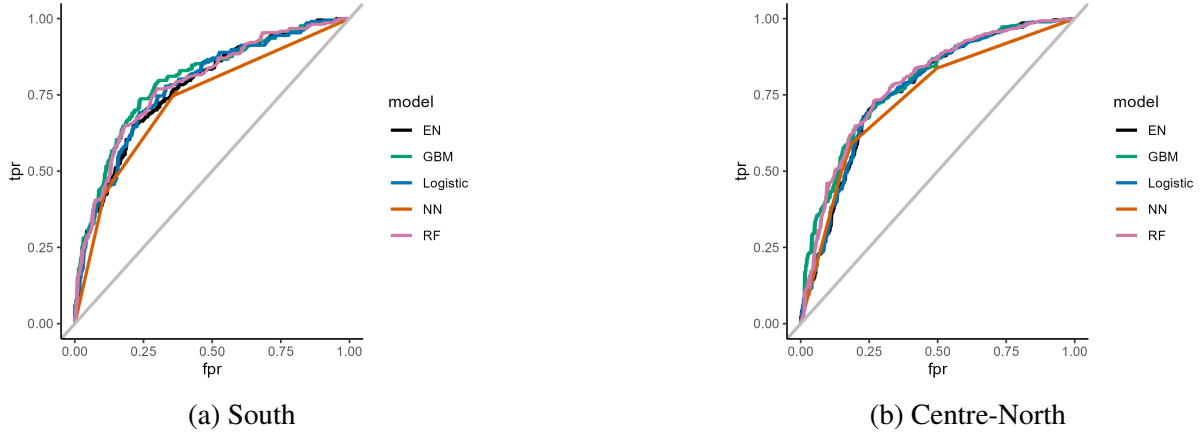
Table 1: Descriptive statistics

	South		Centre-North	
	Mean	sd	Mean	sd
Non-application	0.46	0.50	0.69	0.46
Structural (St)				
Population	8,006.27	29,313.08	5,722.74	25,462.99
Population 0-2	174.42	672.35	117.45	530.17
Population density	300.02	835.48	281.05	506.99
Technical offices expenditure	336,942.01	4,827,467.82	234,868.10	859,467.86
Socioeconomic (SE)				
Income	19,867.90	2,421.53	23,555.41	2,728.91
Share of population with degree or more	0.04	0.02	0.04	0.01
Demand (D)				
Share of foreign's 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	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	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
Institutional Quality Index	0.33	0.14	0.74	0.13
Corruption	0.59	0.16	0.91	0.06
Government effectiveness	0.29	0.13	0.46	0.14
Regulatory quality	0.28	0.18	0.57	0.14
Rule of law	0.33	0.18	0.72	0.16
Voice and accountability	0.39	0.18	0.64	0.10
Politics (Pol)				
Average age of the council	47.23	4.15	50.02	4.74
Share of females in the council	0.31	0.13	0.34	0.12
Average age of assessors	47.23	4.15	50.02	4.74
Share of females among assessors	0.31	0.13	0.34	0.12
Mayor's Age	53.42	10.40	54.75	11.32
Mayor's Education	0.63	0.48	0.40	0.49
Female Mayor	0.09	0.29	0.17	0.37
Seniority of the Mayor	1.85	1.38	1.80	1.05
Political Party				
N	2,274		4,191	

The hyper-parameter optimization is only done on the training set using a repeated (10 times) five-fold cross-validation.⁸ The performance of non-application classification prediction is assessed by analyzing 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

⁸All models have been implemented using R software trained with the optimisation algorithms available through the caret package (Kuhn, 2021).

Figure 2: ROC curves for four ML models and Logistic regression



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.

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.⁹ The AUC in Figure 2 shows that the GBM models outperform all the other ML models, as well as the Logistic regression both in the Southern and Centre-North regions. However, the results of the [DeLong, DeLong, and Clarke-Pearson \(1988\)](#)'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 ($p\text{-value} < 0.05$) solely in the case of the NN model. Consequently, it implies that the performance of RF, EL, and Logit is substantially on par with that of the GBM model.

⁹In 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 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 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.

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 regions, figures which are in the range between ‘fair’ and ‘moderate’ strength of agreement about the prediction reliability (Altman, 1990; Landis & 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, with the exception of the Elastic Net in center-northern regions (P-value = 0.115). Table A2 in the Appendix shows that good prediction performances can be obtained also with a single predictive exercise, i.e. using all the municipalities without the South-Centre-Nort splitting.

These findings indicate the feasibility of predicting municipalities that will not participate in the calls. Both for Southern regions and Centre-North areas, the best performer model in terms of accuracy is GBM, while other algorithms show slightly lower performance. This aligns with 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 & Vaquero-Piñeiro, 2022). Furthermore, in terms of accuracy, Table 3 also shows that the Logistic regression exhibits good performances overall. This result is in line with studies that have found that, in some binary cases, ML methods do not outperform simple logistic regression (Christodoulou et al., 2019). While achieving similar performance to logistic regression, other tested algorithms bring added benefits such as increased flexibility, the ability to handle complex data relationships, and adaptability to diverse patterns. These non-parametric algorithms can uncover intricate patterns that logistic regression might struggle to capture. 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 models available in the literature.

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.

4.2 The Determinants of Inertia

This section presents an elaboration of the feature importance in the prediction of inertia of local governments. In this task, we implemented the GBM, which is the model with the higher area under the ROC curves (see Figure 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 fine-tuned through ten repetitions of five-fold cross-validation on the training set.¹⁰ The focus of this section will be on two main aspects: the Feature Importance (Section 4.2.1) and the Partial Dependence (Section 4.2.2)

4.2.1 The Feature Importance

Results of the features' importance are shown in Figure 3. In this case, there are some differences between the Southern and the Centre-North areas (the correlation between the features' importance is 0.609).

The most important factor in Centre-North and the second important factor in the South is the population size, meaning that the dimension of the municipality plays an important role in its inertia to compete for cohesion calls for funding. The first important factor in Southern municipalities and the second in Centre North is the population 0-2. On this point, it is possible that many municipalities that have low coverage are not particularly interested in obtaining funds to open a nursery because they have very few children under 3 years (this will be further investigated in section 4.2.2 by the Figure 4). The third important factor on average is population density, which is strongly connected to urbanization, an indicator that has been recognized

¹⁰Hyperparameters Best Tune are reported in footnote 9. The GBM regression has been implemented in R, using the `gbm` package (Greenwell, Boehmke, Cunningham, & Developers, 2019).

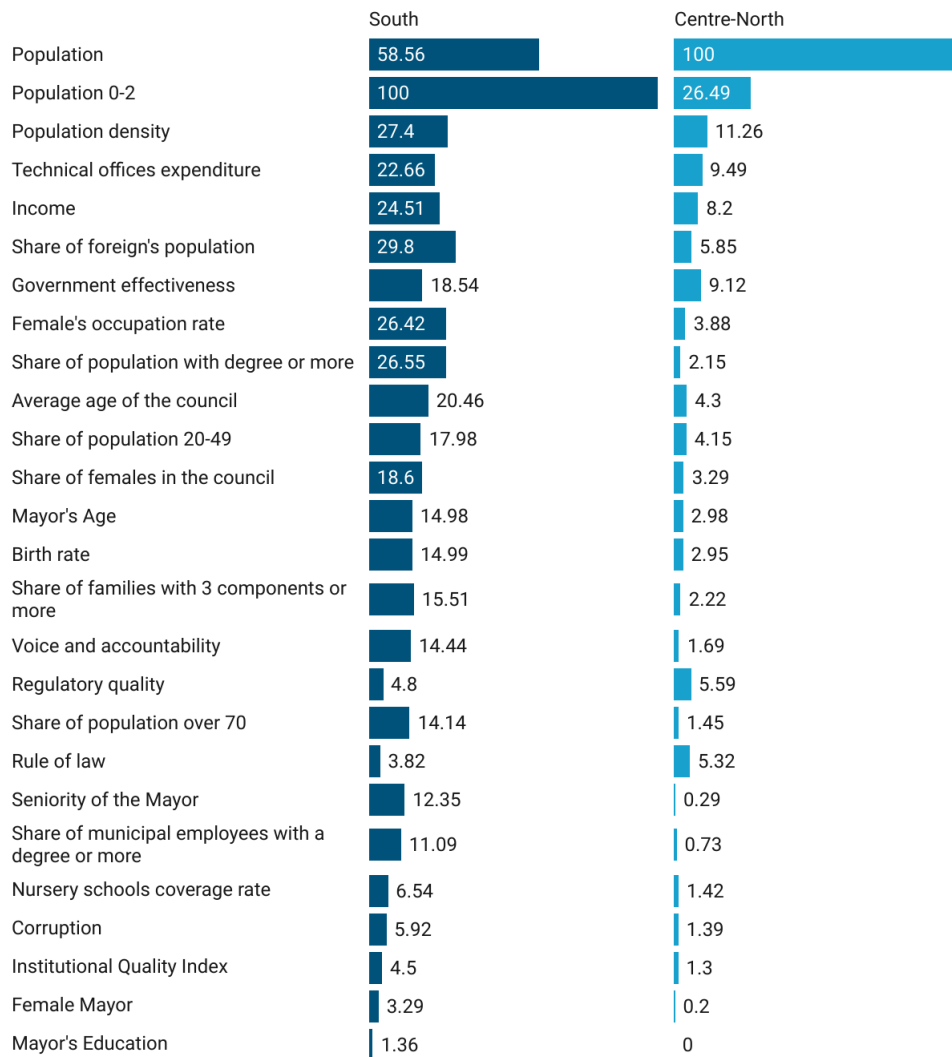
as crucial for the effectiveness of the cohesion policy (Albanese, Carrieri, Ferrara, & Speziali, 2023). In particular, the predominant role of population size and density in both Southern and Centre-North regions is in line with studies showing a different effect of the cohesion policy in urban and rural areas, as highlighted by Gagliardi and Percoco (2017) and Albanese, de Blasio, and Locatelli (2021). Then, the population-related features are followed by technical office expenditure, which is directly connected with the budget of the office in charge of developing projects.

In southern municipalities, the initial three population-related characteristics collectively contribute to approximately 40 percent of total importance, while in center-northern municipalities, they account for 68 percent of overall importance. To gain a deeper understanding of their relevance, we conducted an experiment using a model that exclusively incorporates these three features to predict local government inertia. The performance results of this model are presented in Table A3 and align closely with the outcomes of the primary model illustrated in Table 3. This validation underscores the significance of structural-demographic factors and highlights the efficacy of machine learning methodologies, particularly in low and middle-income countries where only a limited set of indicators is typically accessible.

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 more than non-foreign population because they are less likely to have a family network that can assist the children (Mussino & 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. If these factors have a sign that is positively correlated with the call participation, i.e., the municipality participates because there is a need to satisfy the demand coming from citizens, these results give rise to some concern about the appropriateness of using cohesion (extraordinary) funds to cover something that needs to be covered by standard public expenditure.

Other significant factors explaining the inertia in both Southern and Centre-Northern municipalities are connected to the institutional quality as measured by Nifo and Vecchione (2014) and by the education level of municipal employment. 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). This evidence is also supported by the important role played by individual characteristics of local policymakers as the proportion of females in the council, the age of the Mayor, and the average age of the council. Regarding age, Alesina, Cassidy, and Troiano (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 & Duflo, 2004; Hernández-Nicolás, Martín-Ugedo, & Mínguez-

Figure 3: Feature importance with the best model (GBM)



Gradient Boosting Machine 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 ranked on the average importance between South and Centre-North.

Vera, 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 & Gathmann, 2015). Moreover, our result on the important role of local policymakers in the cohesion policy is in line with the recent literature that introduced political economy elements into the cohesion debate (Buscemi & Romani, 2022; D'Amico, 2021).

Finally, important factors for predicting inertia in both Southern and Center-Northern municipalities are directly connected to socioeconomic development such as the level of education and the level of income. Overall, these features' importance confirm 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 (Aiello, Reverberi, & Brasili, 2019; Becker et al., 2013; Rodríguez-Pose & Garcilazo, 2015). Our result corroborates previous findings by showing that these factors influence the inertia of local governments to participate in cohesion calls.

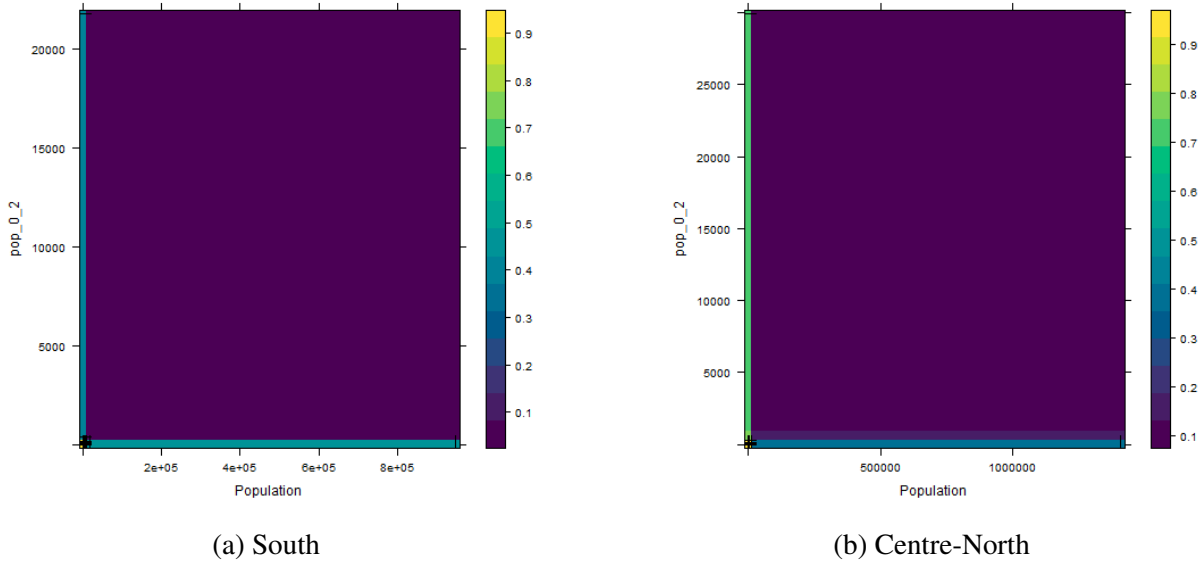
4.2.2 The Partial Dependence

Figure 3 highlights the importance of the features, but does not provide insight into the sign of the relationship between the features and the inertia of local government. In this section, we deepen the sign of the association between features and the outcome of interest leveraging the partial dependence (i.e., marginal effect) plots. By relying on a partial dependence plot (PDP) we could graphically disentangle this relationship without the necessity of a previous mathematical model in the functional relationship also identifying possible non-linearity. In this exercise, we only consider the most important factors explaining the inertia of local government as shown in Figure 3.

Figure 4 shows the partial plots for Population and Population 0-2 years old. It is evident that they 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 0-2. This may be partially connected to the lack of administrative capacity of smaller local governments, unable to plan in the medium to long term. The influence of the population aged 0-2 years 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.

Figure 5 shows the partial plots for the birth rate and the proportion of the foreign population, which are two factors directly connected to the demand for nursery services. 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. 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 could be partly connected to the heterogeneity in the availability of services and cultural differentiation between the two areas. Overall, the positive role of demand-related factors raises apprehensions regarding the suitability of allocating cohesion (extraordinary) funds to address issues that should ideally be addressed through regular public expenditure. This prompts consideration of the appropriateness of using specialized funds to

Figure 4: Partial Dependence Plots for Population and Population 0-2 years



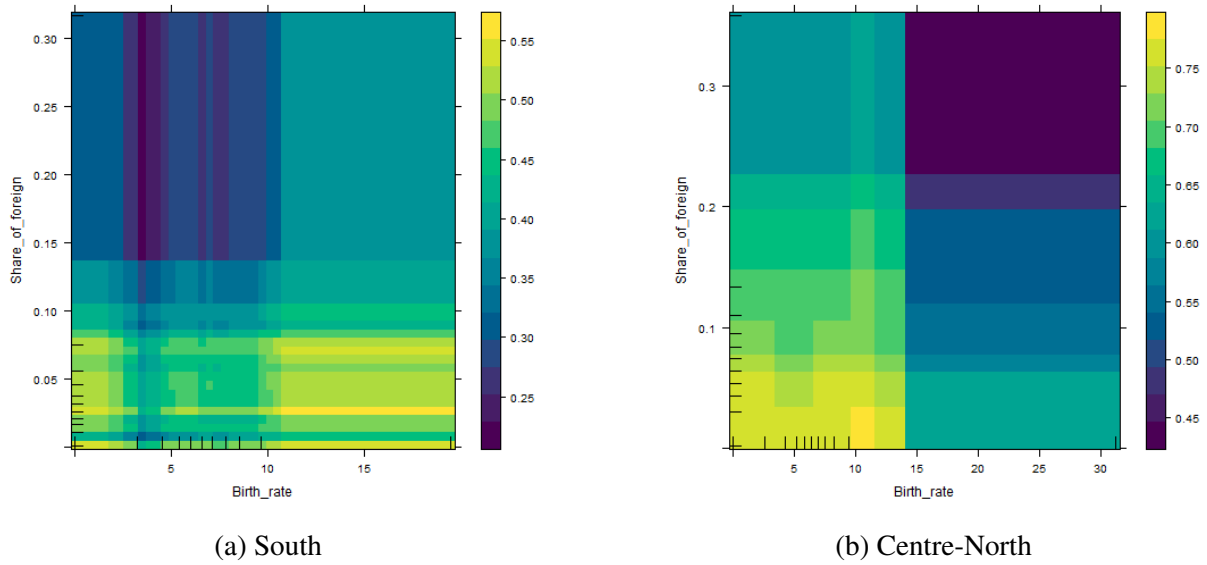
GBM model trained on the whole database. The Partial Dependence Plots are developed in R by the pdp package ([Brandon, 2017](#)).

address needs that are typically within the purview of standard government budgetary allocations.

Figure 6 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 behavior of local governments exhibits a distinctive pattern, and this pattern varies significantly between the Northern and Southern 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. Different factors may contribute to these results. Of course, income level is a proxy for development, but also high-income people may be less likely in need of childcare services. Overall, these nuanced variations in the impact of income on local government inertia underscore the complexity of regional dynamics and emphasize the importance of considering non-linear algorithms in policy analysis.

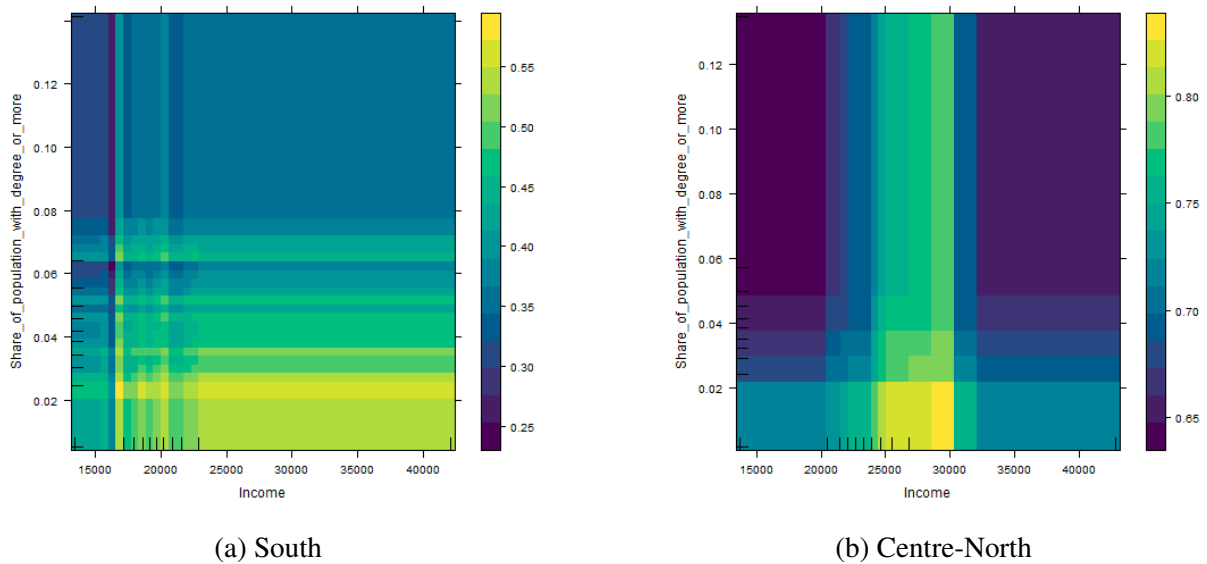
In both areas of the country, the institutional quality indicators as measured by [Nifo and Vecchione \(2014\)](#) appear to be among the most important predictors of local government inertia in leveraging funding opportunities. In Figure 7 we show the PDP for the first two Institutional Quality Index components that are most important in average (Figure 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.

Figure 5: Partial Dependence Plots for Birth Rate and Share of Foreign Population



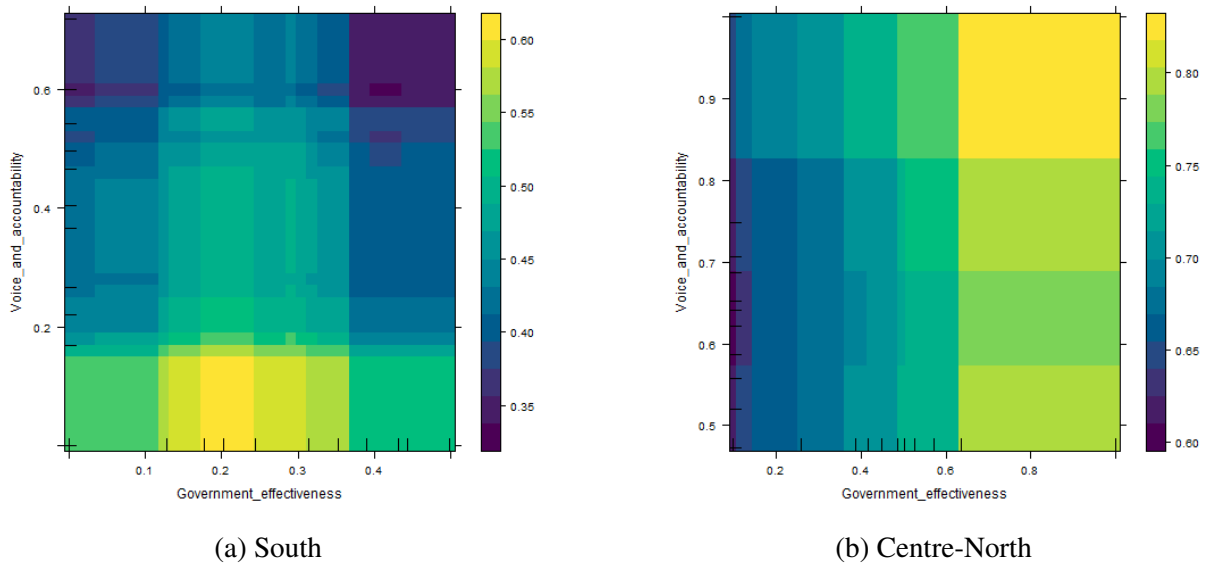
GBM model trained on the whole database. The Partial Dependence Plots are developed in R by the pdp package (Brandon, 2017).

Figure 6: 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).

Figure 7: 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).

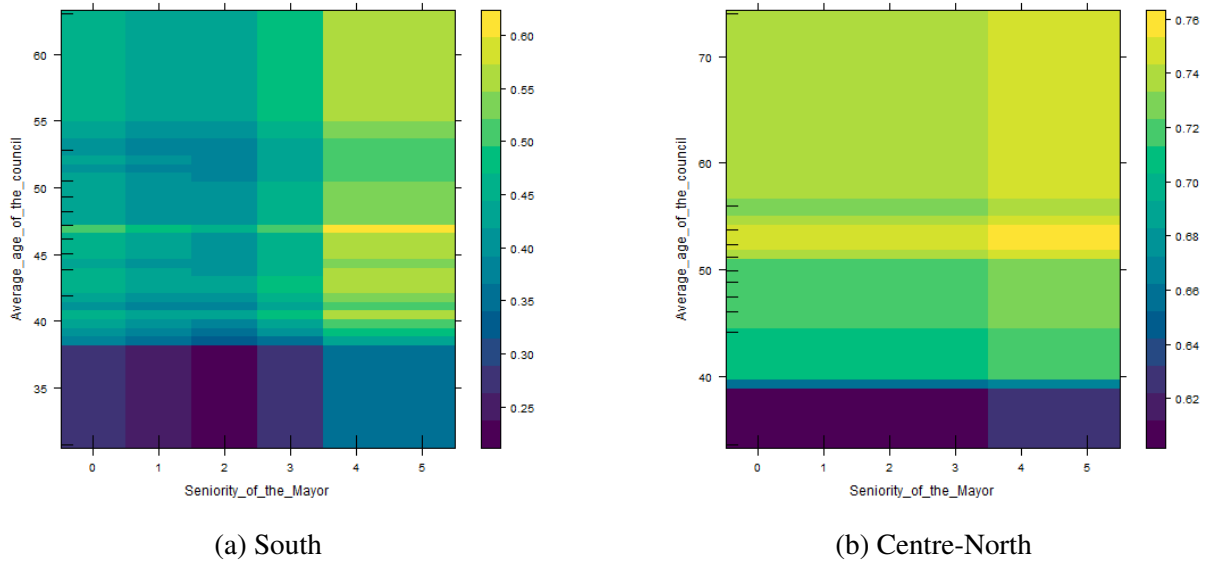
This may depend on the fact that the institutional quality is, on average, higher in northern regions (this can be also noted by comparing the axes of the two panels in Figure 7), and the fact the institutional quality has lower heterogeneity in northern regions. To a certain degree, it appears that 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.

Figure 8 shows the PDP for two of the most important political features: the seniority of the mayor (years in charge)¹¹ and the average age of the council. Regarding average age, in both areas, younger politicians (particularly those under 40) are less likely to miss the funding opportunity. 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). 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 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 wouldn't reach completion before the upcoming election. Within the northern municipalities, we observe a decline in inertia as the length of a politician's service term increases. This pattern could be indicative of a reduced level of self-interest among local politicians in this context.

Figure 9 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

¹¹Article 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.

Figure 8: Partial Dependence Plots for Seniority of the Mayor and Average Age of the Council



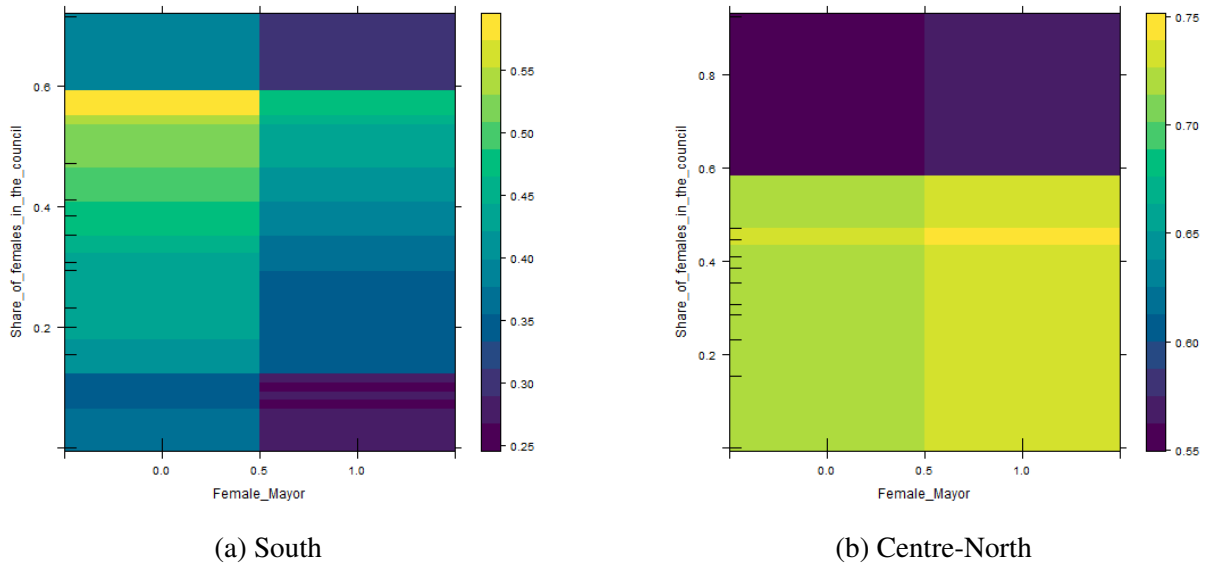
GBM model trained on the whole database. The Partial Dependence Plots are developed in R by the pdp package (Brandon, 2017).

council. The first factor is differentiated between Southern and Centre-Northern municipalities. In the south, female mayors are less likely to lose financing opportunities, and this is in line with the literature showing that women in politics are usually more concerned about peoples' well-being, in particular with services that can support gender equality (Chattopadhyay & Duflo, 2004; Funk & Gathmann, 2015; Hernández-Nicolás et al., 2018). This positive association is not confirmed in the Centre-Northern area of the Country, whilst impacting the percentage of females in the council, even more than in the southern municipalities. This is likely because having a greater representation of women on a council can mean that women's perspectives and experiences are more widely considered when making policy decisions rather than a unique leadership that, in structures characterized by high masculinity, may be more limited in influencing specific policies.

Finally, in Figure 10 we show the Technical office expenditure in relation to the Coverage of nursery schools.¹² These plots reveal that in the Centre-North there is a negative correlation between the expenses for technical offices and the inertia of local administration. Conversely, in the southern municipalities, the inertia is not a problem of resources: high levels of resources spent in technical offices are not compensated for by greater efficiency. Moreover, paradoxically, in southern municipalities, we observe slightly reduced levels of reluctance to respond to the call in areas with greater nursery school coverage. This evident case of increasing need and reduced demand (allocation) paired with diminishing resource allocation is unique to southern municipalities and is not mirrored in their northern counterparts.

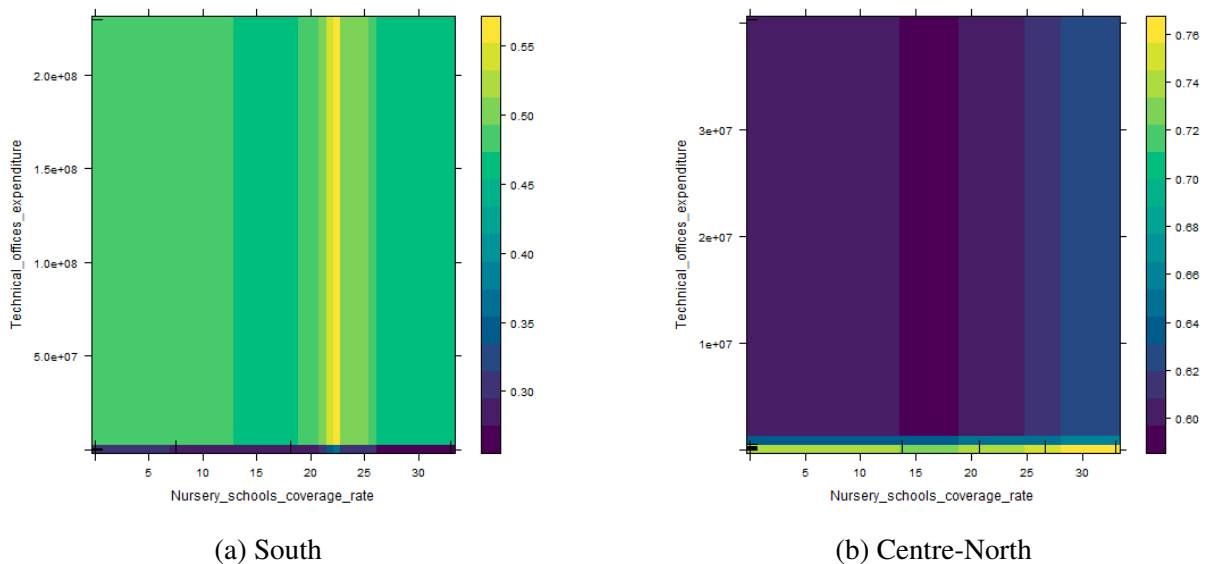
¹²We use the total value of technical office expenditure but we observe the same results on per capita expenditure for technical office. Results are available upon request.

Figure 9: 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](#)).

Figure 10: Partial Dependence Plots for Coverage of Nursery Schools and 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 delves into the intricacies of predicting which local governments, despite their need, are likely to miss out on funding opportunities. In this regard, open calls within the Italian National Recovery and Resilience Plan (NRRP), 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 results indicate a strong capability to accurately predict which local government entities are less inclined to participate in cohesion initiatives. Furthermore, the empirical findings underscore the relevance of territorial structural features, with population size and population 0-2 emerging as crucial factors in predicting the inertia of local governments. Territories characterized by a limited number of children and a potential boost in birth rates through the presence of nursery schools are more prone to non-participation. This poses a substantial missed opportunity for local development, especially given that the investment required no co-financing. It's noteworthy that the study exclusively focuses on municipalities with insufficient service coverage (LEP less than or equal to 33 percent). Additionally, factors tied to the demand for services, such as female occupation rate and birth rate, play a significant role. Moreover, the results highlight the multifaceted nature of the issue, emphasizing the influence of local institutional quality, income, education levels of the resident population, and individual characteristics of policymakers.

This analysis provides valuable insights for policymakers and practitioners, offering a nuanced understanding of the dynamics that contribute to the under-utilization of available funding. Identifying in advance potential no-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 the existing cohesion framework, these predictions can be employed to target direct assistance, aiding the local government in promptly formulating appropriate plans, programs, and projects.

The research contributes to the broader discourse on place-based policies and the challenges associated with ensuring effective utilization of funds aimed at addressing regional disparities. By exploring the under-participation of local authorities in competitive funding opportunities, the study provides a foundation for developing targeted interventions to overcome inertia and enhance the impact of policy initiatives. Moreover, the application of machine learning in predicting funding allocation challenges opens new avenues for research and policy development in the field of public programs and spending.

As nations strive to implement cohesion plans and address pressing societal issues, the findings of this study offer actionable insights for optimizing the allocation of funds to diverse local governments with varying needs. In this regard, in many cases, more fragile territories that have more need to invest are not able to compete, thus missing opportunities. A system of fund distribution based on competitive calls can penalize areas where there is a greater need for investment because participation in the call is negatively influenced by variables that would justify, in practice, the allocation of funds. By understanding the factors influencing inertia, policymakers can tailor interventions to encourage participation where it is most needed, ultimately fostering more effective and equitable development outcomes.

This study advocates a reevaluation of the importance of competitive calls within cohesion policies. Examining the specific case study and acknowledging kindergartens as essential services leads to questioning the reasoning behind funding them through competitive calls. In general, the existing institutional framework for European cohesion policies, primarily the distribution of funds to regional governments, establishes a mediation mechanism where the effectiveness of local institutions plays a crucial role. The combination of multilevel governance and limited administrative capacity in certain regions, which struggle with medium to long-term planning, may jeopardize the optimal utilization of cohesion resources. In simpler terms, a bottom-up approach funded through top-down resources might not be the most effective solution.

In the broader policy context, the research suggests a reconsideration of the balance between decentralized approaches and a more centralized policy that can identify territorial needs, particularly in cases where weak institutional capacity hampers local administrations. Such a shift could prove advantageous for investments capable of promoting economic convergence and addressing the development disparities between advanced and impoverished regions. The persistence of underdevelopment in some regions is closely linked to local institutions, underscoring the crucial importance of policies that can withstand and succeed despite these local dynamics.

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Appendix

Table A1: Data source

Variable	Year	Source
Call participation	2020	Ministry of Education and Excellence
	2021	PNRR Istruzione
Population	2019	Istat
Population 0-2	2021	Istat
Population density	2020	Istat
Technical offices expenditure	2021	openpolis processing on openBDAP data
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
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	2021	Ministry of the Interior
Share of females in the council	2021	Ministry of the Interior
Average age of assessors	2021	Ministry of the Interior
Share of females among assessors	2021	Ministry of the Interior
Mayor's Age	2021	Ministry of the Interior
Mayor's Education	2021	Ministry of the Interior
Female Mayor	2021	Ministry of the Interior
Seniority of the Mayor	2021	Ministry of the Interior
Political Party	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 A2: 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.

Table A3: Models' performances using only 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.