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Mafia, Politics & Machine Predictions

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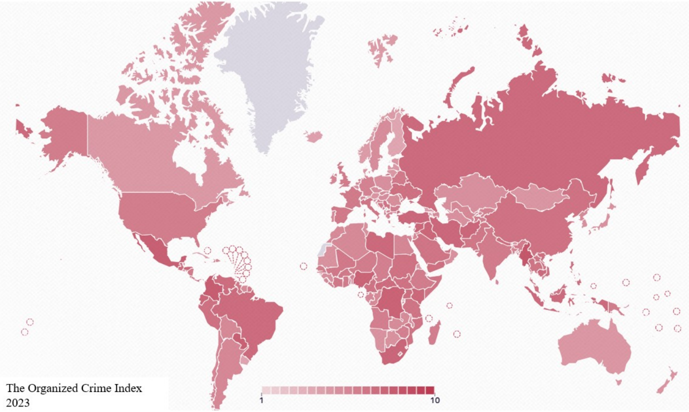
Motivation

- 80% of the global population lives in countries where organized crime (OC) presents a high risk [Organized Crime Index, 2023], with negative effects on society, e.g. economic growth, human capital, influence on **politics** [Alesina et al., 2019; Daniele and Dipoppa, 2017; Pinotti, 2015b; Sviatschi, 2022]



Problem: Detection and Measurement

- **It is difficult to fight OC because detection is imperfect and costly** [Pinotti, 2015a; United Nations Office on Drugs and Crime, 2016]
  - Illegal phenomenon
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- In turn, OC measurement is imperfect
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Can we use machine learning (ML) to create a measure of OC presence in politics?

Can we use this new measure to facilitate detection and study OC influence on politics?

What we do: focus on OC and Politics

- By leveraging ML algorithms, we predict local governments in Italy with a high risk of mafia infiltration
    - We create a synthetic measure of mafia infiltration in politics based on city council dismissals for mafia infiltration by the national government
    - We propose this indicator as a tool to improve the detection of mafia infiltration in local politics

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- By leveraging ML algorithms, we predict local governments in Italy with a high risk of mafia infiltration
  - We create a synthetic measure of mafia infiltration in politics based on city council dismissals for mafia infiltration by the national government
  - We propose this indicator as a tool to improve the detection of mafia infiltration in local politics
- A stronger state presence... Does a public spending shock discourage or promote OC influence on local politics?
  - An increase in public investments might promote economic growth, reducing the grip of OC
  - More spending might attract OC into politics

Preview

- ML to predict mafia infiltration in local politics measured by city councils dismissals for mafia infiltration:

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    - Focusing on the top 4.5% (1%) of the predicted risk in a given year, that is 360 (72) municipalities, we ensure recall that is on average around 89% (50%), with the true positives on average being around 15% (28%).

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  - City councils dismissals for mafia [Acconcia et al., 2014; Daniele and Geys, 2015; Fenizia, 2018; Galletta, 2017]

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  - City councils dismissals for mafia [Acconcia et al., 2014; Daniele and Geys, 2015; Fenizia, 2018; Galletta, 2017]
- Redistributive policy (EU funds) and economic development [Alesina and Perotti, 2002; Becker et al., 2010a]
- Rapacity effect [Dube and Vargas, 2013]
- Machine learning in economics [Ash et al., 2020; Athey, 2018; Glaeser et al., 2016; Kleinberg et al., 2018; Mohler et al., 2015]

Part I:
Mafia Infiltration and Machine Predictions.

City council dismissals

Since 1991, the Italian authorities can dismiss a city council if there is evidence of mafia infiltration, specifically:

- Direct/indirect contacts of local politicians with organized crime groups
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Based on a clue, phone calls traced

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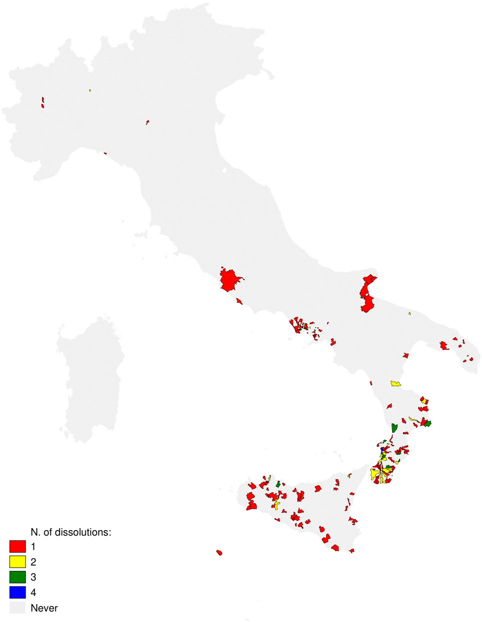
Geographical distribution of dismissals



Predictive Design

- Predicting **detected** mafia infiltration (yearly, municipal-level)
- Y is constructed as follows:
  - 1 if a city council was dissolved during the mandate of the mayor
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▸ Dissolved Councils and Infiltration distribution over time

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- Nine algorithmic approaches (LR, Lasso, Ridge, Elastic Net, DT, RF, GBoosting, XGBoost, DNN)
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- A municipal-year observation is infiltrated if the prediction is >0.5
- Prediction phase/optimization $\longrightarrow$ Explainability
    - SHAP: Global and local interpretability of ML models ▸ Details

Machine Learning Approach

- **Chosen metric: Recall** (i.e., maximize true positives or penalize false negatives)

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- Alternative metric: Precision

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

A Highly Unbalanced Problem

Sampling	Y=0	Y=1	% (Y=1)
Original	105,596	887	0.83
SMOTE	105,596	105,596	50.00
ADASYN	105,582	105,596	49.99
SMOTE+Tomek	105,595	105,595	50.00

- Challenging prediction application: highly unbalanced distribution → synthetic oversampling in the training set
- In the test set the distribution remains identical (Y=1 is 0.83% of the total observations)

▸ Details ▸ Infiltration distribution over time

Feature Space

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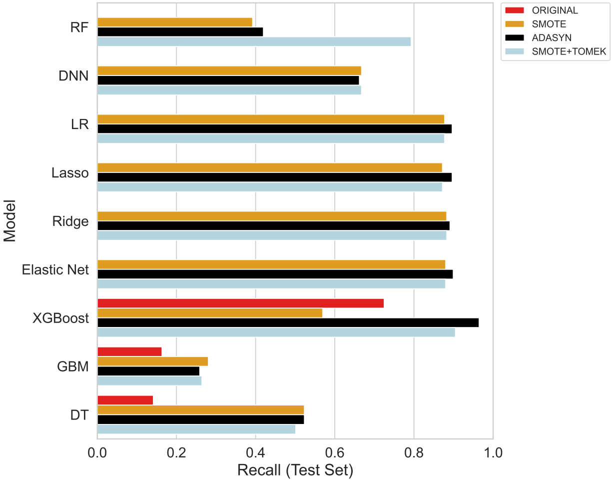
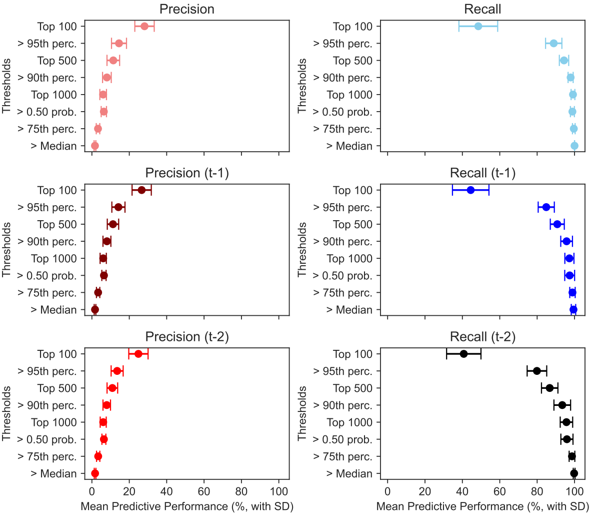
  - We differentiate across different versions of the spending variables (e.g. current and capital spending) ▸ Details

Prediction Performance: Recall



▸ Revoked Vs Confirmed dismissals

Recall and Precision for Various Rankings, by Year



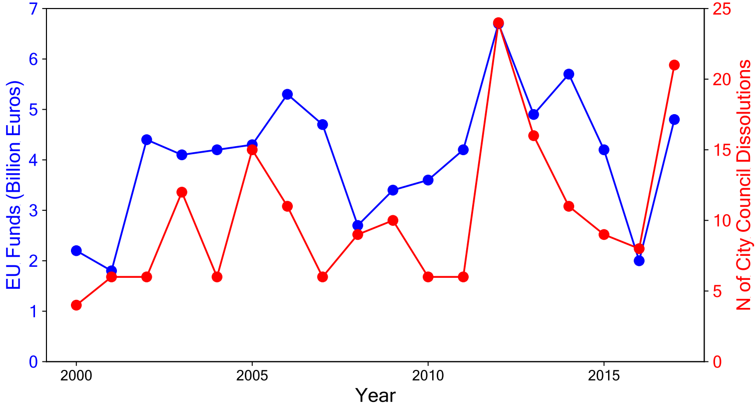
▸ By macro-regions ▸ Where we contribute

Additional Results

- Which are the most relevant predictors? ▸ Global SHAP ▸ Local SHAP ▸ Example
- Variation across time and space ▸ Map
- Variable distribution ▸ Graph ▸ Graph across macro-regions
- External Validity ▸ 2021-2023 Prediction
- Variation around the dismissal ▸ Prediction dynamics
- Correlations with other crimes ▸ Correlations
- Additional ML exercises ▸ Table
- Random Seeds ▸ Graph

Part II: Redistributive policy and on mafia infiltration in politics

A stronger State presence



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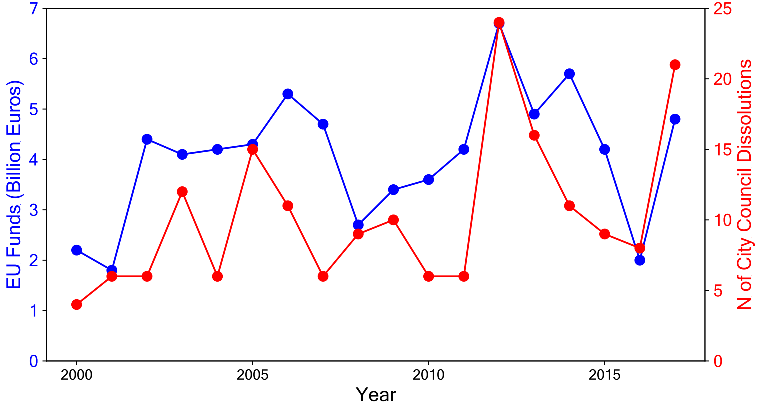

- Does a positive shock in public spending affect mafia infiltration in politics?
  - Transfers can either foster economic growth, reducing the grip of mafia, or they might push mafia toward local governments managing new funds
- Why do transfers promote growth in some areas and not in others?
  - Becker et al [2010b] show EU funds worked in most areas but limited effect in Southern Italy

Transfers windfall and Mafia

We study if and how a transfers windfall affects mafia presence in local politics:

- The 2007-2013 EU funds
- Funds are disproportionally allocated to "convergence" regions, i.e. regions with a GDP below 75% EU average - Southern regions
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We target the impact of the 2007-2013 wave which may have affected the risk of mafia infiltration via two main channels:

- Larger budget (i.e., more economic resources assigned) ▸ Graph
- Increased decentralization in spending decision (local institutions are key spending authority) & higher flexibility in implementation/simplification of rules
- Municipalities can invest more in capital spending and provide more subsidies to local firms/NGOs

Identification

Identification: Diff-in-Disc

$$\begin{aligned} \text{Infiltration}_{i,t} = {} & \alpha + \beta \text{Treated}_i \times \text{Post2006}_t + \eta f(\text{Distance}_i) \times \text{Post2006}_t \\ & + \gamma \text{Treated}_i \times f(\text{Distance}_i) \times \text{Post2006}_t + FE_i + FE_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

- Infiltration$_{i,t}$= Infiltration risk for municipality *i* in year *t*; period 2001-2013, treatment since 2007
- We consider municipalities in 4 regions: Lazio and Molise for center Italy, and Campania and Puglia for southern Italy: Treated$_i$, i.e., being a southern municipality
- f(Distance), i.e., a local polynomial of the distance in Km from the border defined for different bandwidths: 5, 10, 25, 50, and 100 km and the entire region. Either linear or quadratic specification
- We use a triangular kernel to weigh observations
- $FE_i + FE_t$ are municipality and year fixed effects
- $\varepsilon_{i,t}$ standard errors are either clustered at the municipal level or computed by bootstrapping

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The spatial diff-in-disc [Butts, 2023] has three main advantages in our context, as it reduces...:

- ...the effect of any potential unbalancing around the administrative discontinuity in time-fixed/slowly changing characteristics

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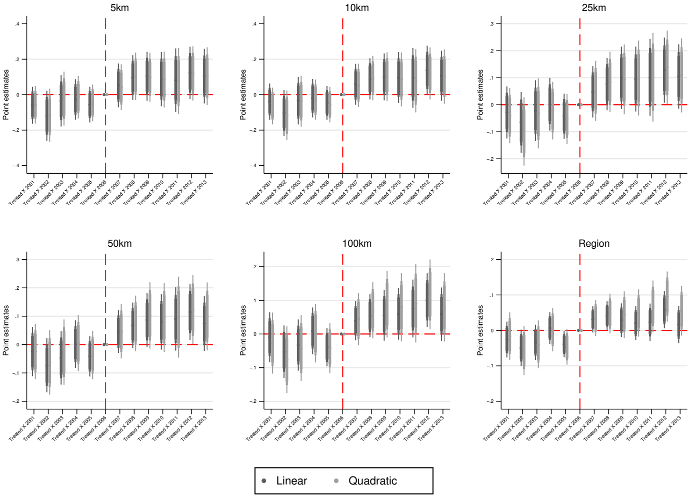
- Parallel trend assumption between treated/control municipalities
- Changes in covariates induced by the treatment balance between T and C

▸ Balancing

Results: Diff-in-Disc

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.
Treat X Post 2006	0.142***	0.132***	0.138***	0.141***	0.120***	0.138***	0.111***	0.115***	0.084***	0.112***	0.055***	0.083***
	(0.040)	(0.041)	(0.038)	(0.040)	(0.033)	(0.037)	(0.026)	(0.033)	(0.020)	(0.027)	(0.012)	(0.017)
Observations	1,298	1,298	2,023	2,023	3,934	3,934	7,105	7,105	10,904	10,904	17,111	17,111
R-squared	0.701	0.706	0.700	0.700	0.723	0.724	0.784	0.784	0.822	0.823	0.806	0.806
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.0757	.0887	.0646	.0648	.0471	.0502	.0452	.0453	.0438	.0455	.0482	.0495
Bootstrap	.0006	.0018	.0008	.001	.0002	.0004	0	.0009	.0001	.0001	0	0
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.17	.17	.15	.15	.12	.12	.11	.11	.11	.11	.1	.1

Results: Event Study



Additional Tests

- Placebo with fake borders Figure
- Robust coefficient Table Figure
- Random Seeds Table
- Placebo: EU Funds but no risk of Mafia Infiltration Table
- Removing capital spending from the prediction Event Study
- Removing 2007-2013 from the training set Table
- Mafia-related crimes Table Event Study Table
- Mechanisms:
  - Lazio Vs Campania (only decentralization) Table
  - Puglia Vs Molise (decentralization + funds increase) Table

Conclusions

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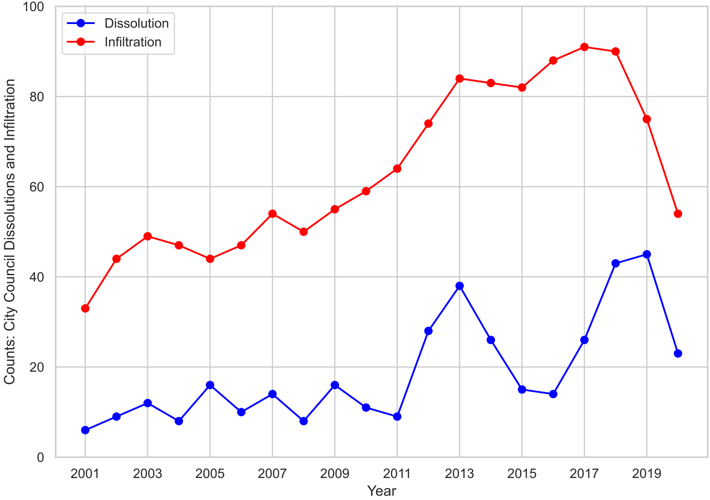
- The 2007-2013 wave of EU funds increased the risk of mafia infiltration in treated municipalities
- The mix of predictive and causal methods offers insights into the effects of increased state presence (transfers) in OC affected areas

> Thanks for attending!

Questions? Comments?

Appendix.

Dissolved Councils and Infiltration distribution over time



▸ Back

ML Explainability via SHAP

- SHAP reveals the most influential features in a model’s prediction output
- It compares the model’s output when a specific feature is included versus when it is excluded
- SHAP provides both local and global measures for each feature, helping us assess its impact on the model’s decisions

▸ Back

SMOTE (Synthetic Minority Over-sampling Technique)

Mathematical Formulation

- Let A be a minority class instance, and B and C be its k-nearest neighbors.
- For each A, generate synthetic instances A' by connecting A with some of its neighbors B or C in the feature space.
- The synthetic instance A' is given by $A' = A + \lambda \times (B - A)$, where λ is a random value between 0 and 1.

▸ Back

ADASYN (Adaptive Synthetic Sampling)

Mathematical Formulation

- Incorporates a density distribution factor to adaptively generate synthetic instances.
- For each minority class instance, calculate the number of synthetic instances to generate based on the density ratio.
- Use the same formula as SMOTE to generate synthetic instances, but with an adjusted λ based on the density distribution.
- Promotes the creation of more synthetic instances for minority instances in denser regions.

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SMOTE-Tomek (Combining SMOTE with Tomek Links)

Mathematical Formulation

- Identify Tomek links, pairs of instances (A, B) where A is the nearest neighbor of B but they belong to different classes.
- Apply SMOTE only to instances involved in Tomek links, focusing on generating synthetic instances for instances that contribute to noise.
- After SMOTE, remove Tomek links to clean the dataset from noisy and irrelevant synthetic instances.

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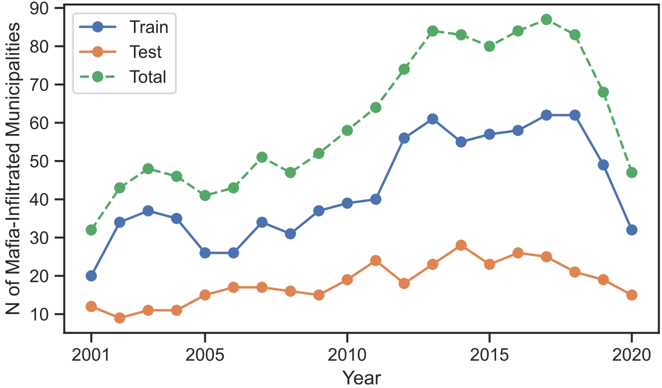
Infiltration distribution over time



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Political Variables

For each municipality election, we have information on:

- Ideology/political placement of winning coalition/party
- Share of votes for winning candidate
- Number of competitors
- Sex of the mayor
- Educational background of the mayor (college degree or not)
- Incumbency
- Birth Location (municipality i or not)

▸ Back

Public Spending Variables/2

For each typology, we construct four variables. Given spending typology x:

- Share of *current* expenses

$$\text{Share Curr. } (x)_{i,t} = \frac{\text{Curr}(x)_{i,t}}{\sum_{x \in X} \text{Curr}(x)_{i,t}} \tag{2}$$

- Share of *capital* expenses

$$\text{Share Cap. } (x)_{i,t} = \frac{\text{Cap}(x)_{i,t}}{\sum_{x \in X} \text{Cap}(x)_{i,t}} \tag{3}$$

- Expense rate

$$\text{Rate}(x)_{i,t} = \left(\frac{\text{Curr}(x)_{i,t} + \text{Cap}(x)_{i,t}}{\text{pop}_{i,t}} \right) \times 10k \tag{4}$$

- Share of *current* expenses out of total expenses:

$$\text{Share Curr. Global } (x)_{i,t} = \frac{\text{Curr}(x)_{i,t}}{\sum_{x \in X} (\text{Curr}(x)_{i,t} + \text{Cap}(x)_{i,t})} \tag{5}$$

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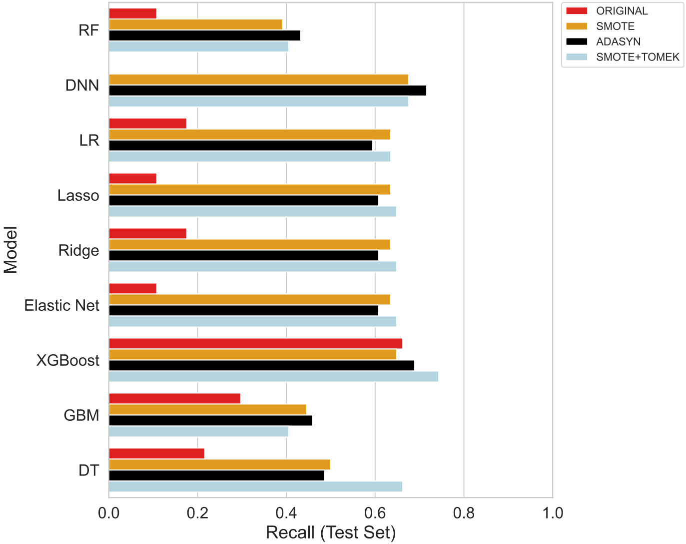
Predictive Performance



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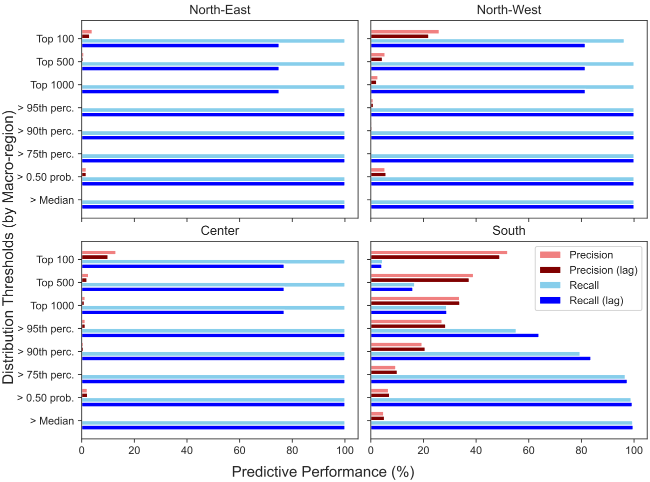
Recall and Precision for Various Rankings, by Macro-Region



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Investigations step

- We can improve the first steps of the detection process, i.e. the probability of starting an investigation (“proactive” instead of “reactive” investigations)

Start of the investigation
Based on a clue, phone calls traced

Investigation
6-months – lead by national police

Dismissal of the city council
By the Ministry of Interior

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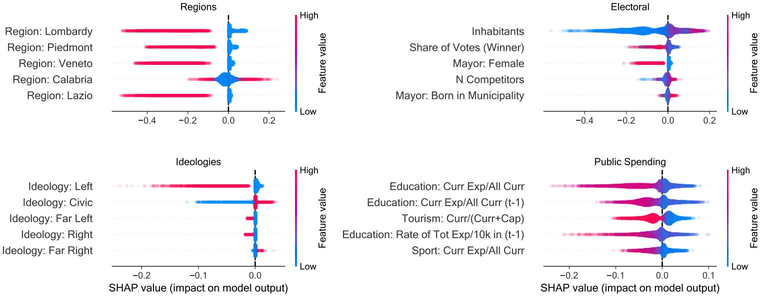
SHAP: Explainability Results



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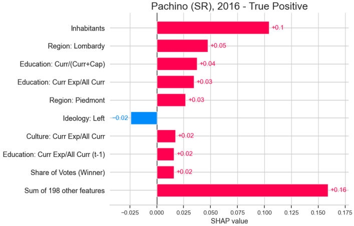
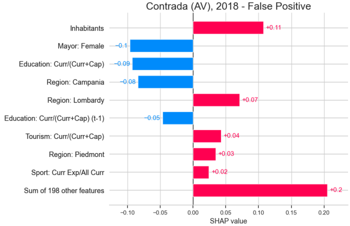
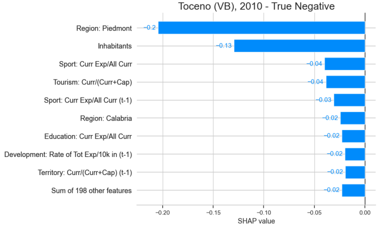
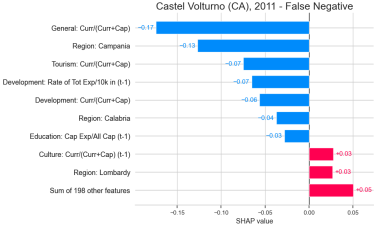
Locally Explainable Predictions


Pachino (SR), 2016 - True Positive


Contrada (AV), 2018 - False Positive


Toceno (VB), 2010 - True Negative


Castel Volturno (CA), 2011 - False Negative

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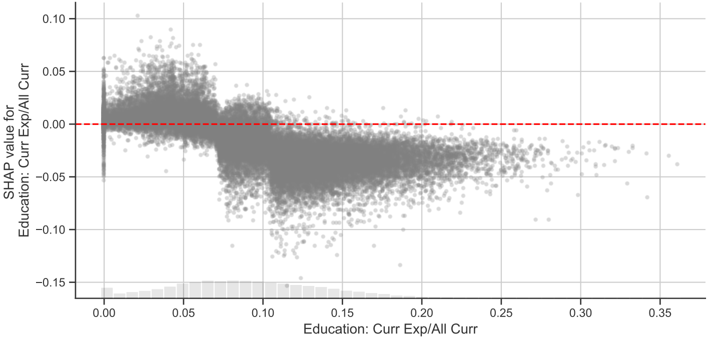
Feature Explainability - Example



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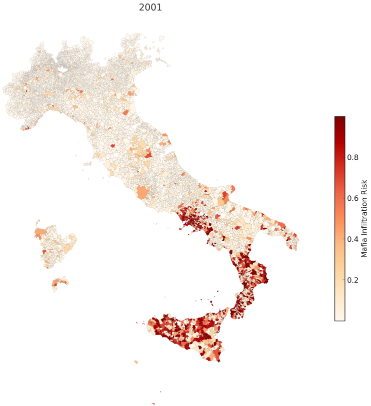
Predicted Infiltration Risk 2001-2020, Distribution in Time and Space



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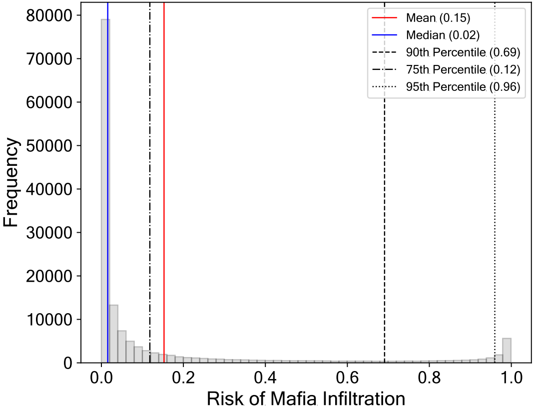
Predicted Infiltration Risk 2001-2020, Distribution



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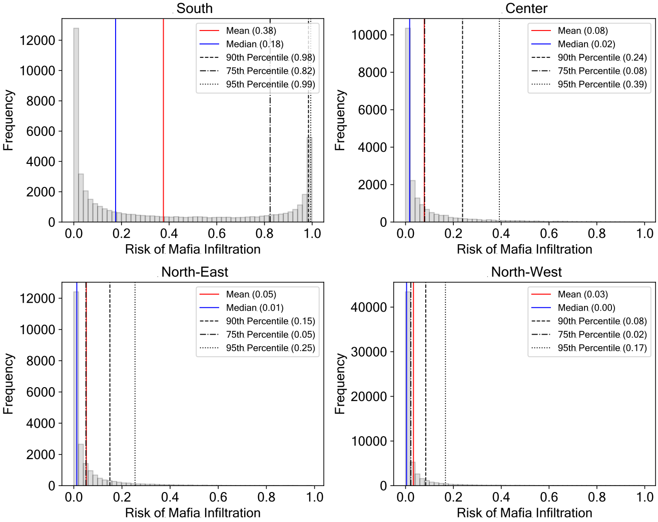
Predicted Infiltration Risk 2001-2020, Distribution (by Macro-Region)



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External Validity: Municipalities Dissolved 2021-2023

Municipality	Region	dismissal year	2020	Avg. 2016-2020	Last term
Squinzano	Apulia	30/01/21	98%	92%	97%
Guardavalle	Calabria	23/02/21	100%	100%	100%
Carovigno	Apulia	12/03/21	76%	76%	82%
Barrafranca	Sicily	16/04/21		100%	
Marano di Napoli	Campania	18/06/21	100%	100%	100%
San Giuseppe Jato	Sicily	09/07/21	81%	53%	42%
Villaricca	Campania	06/08/21	91%	82%	82%
Foggia	Apulia	06/08/21	20%	31%	22%
Nocera Terinese	Calabria	30/08/21	100%	95%	99%
Simeri Crichi	Calabria	30/08/21	99%	99%	99%
Rosarno	Calabria	30/08/21	100%	98%	98%
Calatabiano	Sicily	30/08/21	97%	98%	98%
Bolognetta	Sicily	18/11/21		99%	
Ostuni	Apulia	27/12/21	42%	32%	24%
Castellammare di Stabia	Campania	24/02/22	90%	75%	94%
Trinitapoli	Apulia	05/04/22	65%	51%	65%
Torre Annunziata	Campania	06/05/22	20%	67%	69%
Portigliola	Calabria	22/05/22	0%	5%	5%
San Giuseppe Vesuviano	Campania	09/06/22	100%	92%	99%
Soriano Calabro	Calabria	17/06/22	100%	92%	99%
Neviano	Apulia	05/08/22	53%	41%	53%
Cosoleto	Calabria	21/11/22	33%	12%	13%
Nettuno	Lazio	21/11/22	36%	54%	50%
Anzio	Lazio	21/11/22	81%	71%	80%
Sparanise	Campania	19/12/22	98%	97%	97%
Scilla	Calabria	11/04/23	97%	99%	97%
Castiglione di Sicilia	Sicily	23/05/23	100%	79%	75%
Rende	Calabria	28/06/23	100%	99%	100%
Orta Nova	Apulia	18/07/23	93%	73%	93%
Palagonia	Sicily	09/08/23	93%	93%	92%
Acquaro	Calabria	18/09/23	87%	95%	87%
Caivano	Campania	17/10/23	95%	98%	94%
Capistrano	Calabria	17/10/23	0%	35%	30%

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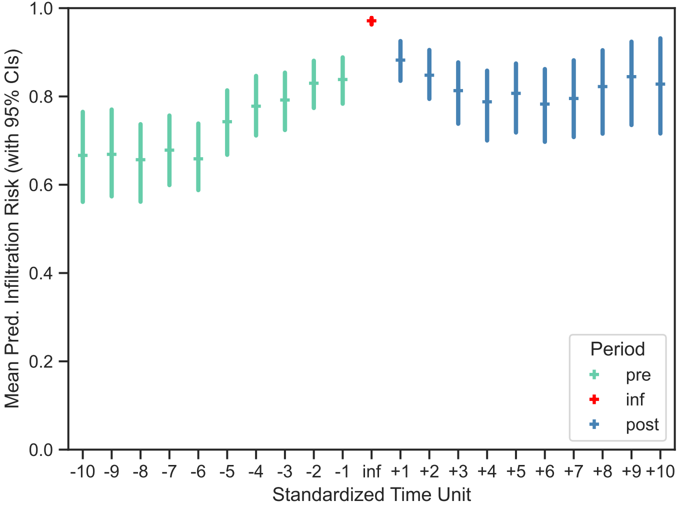
Descriptive Evidence: Predicted Infiltration Risk for Dissolved Municipalities



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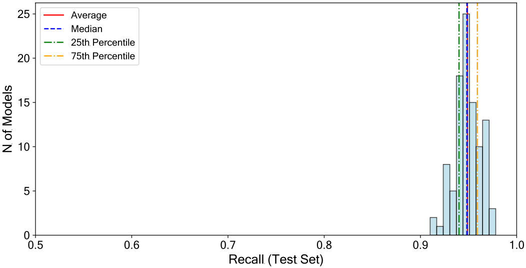
100 random seeds



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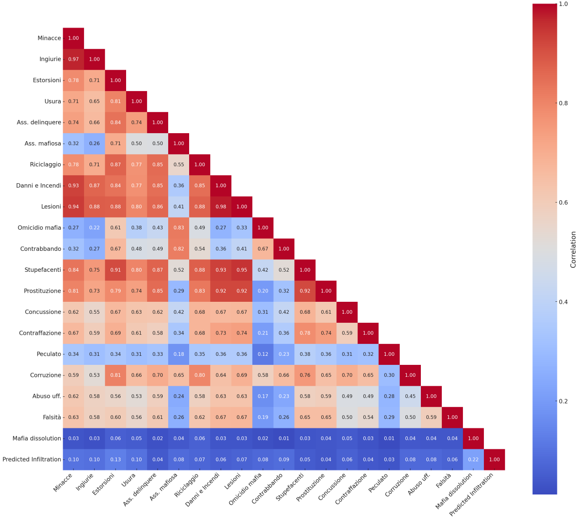
Predicted Infiltration Risk 2001-2020, Correlations



	Minacce	Ingiurie	Estorsioni	Usura	Ass. delinquere	Ass. mafiosa	Riciclaggio	Danni e Incendi	Lesioni	Omicidio mafia	Contrabbando	Stupefacenti	Prostituzione	Concussione	Contraffazione	Peculato	Corruzione	Abuso uff.	Falsità	Mafia dissolution	Predicted Infiltration
Minacce	1.00																				
Ingiurie	0.97	1.00																			
Estorsioni	0.78	0.71	1.00																		
Usura	0.71	0.65	0.81	1.00																	
Ass. delinquere	0.74	0.66	0.84	0.74	1.00																
Ass. mafiosa	0.32	0.26	0.71	0.50	0.50	1.00															
Riciclaggio	0.78	0.71	0.87	0.77	0.85	0.55	1.00														
Danni e Incendi	0.93	0.87	0.84	0.77	0.85	0.36	0.85	1.00													
Lesioni	0.94	0.88	0.88	0.80	0.86	0.41	0.88	0.98	1.00												
Omicidio mafia	0.27	0.22	0.61	0.38	0.43	0.83	0.49	0.27	0.33	1.00											
Contrabbando	0.32	0.27	0.67	0.48	0.49	0.82	0.54	0.36	0.41	0.67	1.00										
Stupefacenti	0.84	0.75	0.91	0.80	0.87	0.52	0.88	0.93	0.95	0.42	0.52	1.00									
Prostituzione	0.81	0.73	0.79	0.74	0.85	0.29	0.83	0.92	0.92	0.20	0.32	0.92	1.00								
Concussione	0.62	0.55	0.67	0.63	0.62	0.42	0.68	0.67	0.67	0.31	0.42	0.68	0.61	1.00							
Contraffazione	0.67	0.59	0.69	0.61	0.58	0.34	0.68	0.73	0.74	0.21	0.36	0.78	0.74	0.59	1.00						
Peculato	0.34	0.31	0.34	0.31	0.33	0.18	0.35	0.36	0.36	0.12	0.23	0.38	0.36	0.31	0.32	1.00					
Corruzione	0.59	0.53	0.81	0.66	0.70	0.65	0.80	0.64	0.69	0.58	0.66	0.76	0.65	0.70	0.65	0.30	1.00				
Abuso uff.	0.62	0.58	0.56	0.53	0.59	0.24	0.58	0.63	0.63	0.17	0.23	0.58	0.59	0.49	0.49	0.28	0.45	1.00			
Falsità	0.63	0.58	0.60	0.56	0.61	0.26	0.62	0.67	0.67	0.19	0.26	0.65	0.65	0.50	0.54	0.29	0.50	0.59	1.00		
Mafia dissolution	0.03	0.03	0.06	0.05	0.02	0.04	0.06	0.03	0.03	0.02	0.01	0.03	0.04	0.05	0.03	0.01	0.04	0.04	0.04	1.00	
Predicted Infiltration	0.10	0.10	0.13	0.10	0.04	0.08	0.07	0.06	0.07	0.08	0.09	0.05	0.04	0.06	0.04	0.03	0.08	0.08	0.06	0.22	1.00

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Additional ML exercises

Table: Predictive results of additional ML exercises

Configuration	Obs (% Y=1)	Sampling	Recall	Roc-Auc	Precision
Southern Regions	51,023 (2.31)	Original	0.776	0.841	0.165
		ADASYN	0.903	0.843	0.089
Dissolved Municipalities	3,724 (32.81)	Original	0.932	0.613	0.392
		ADASYN	0.953	0.620	0.395
Dissolved Municipalities (No Yrs After Dissolution)	2,509 (43.76)	Original	0.942	0.697	0.573
		ADASYN	0.955	0.697	0.570
Cross-sectional	7,755 (2.41)	Original	0.357	0.670	0.349
		ADASYN	0.696	0.822	0.246

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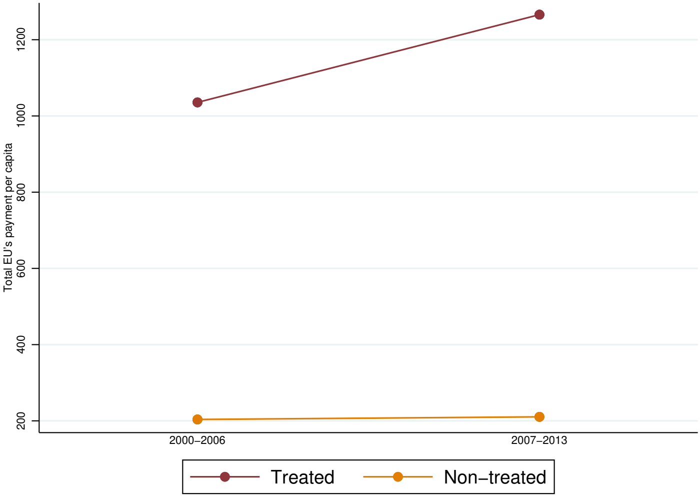
Dynamics of EU Funds



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Identification: Balancing

	5 Km		10 Km		25 Km		50 Km		100 Km		Region	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Avg. change population	0.114	0.077	0.109	0.124	0.072	0.132	0.028	0.068	0.023	0.042	-0.098	0.027
Household size	0.006	0.007	0.000	0.005	-0.006	-0.005	-0.007	-0.005	-0.010	-0.010	-0.003	0.003
Aging rate	9.594	9.893	13.268	10.338	15.656	14.563	10.717	15.932	0.730	12.491	-10.216**	-4.822
Poor families	0.018	0.078	-0.110	0.022	-0.199	-0.142	0.027	-0.164	-0.250	0.025	-0.550***	-0.559***
College rate (30-34)	-1.619	-1.340	-1.975	-1.360	-3.030**	-2.365*	-3.855***	-3.029**	-4.347***	-3.929***	-4.131***	-4.688***
Dropout rate	-2.472	-2.588	-3.020	-2.374	-3.459**	-3.181*	-3.670***	-3.787**	-3.168***	-3.826***	-3.000***	-2.316**
Unemployment rate	0.341	0.429	0.171	0.307	-0.105	-0.054	-0.047	0.016	-1.261*	0.062	-2.347***	-2.327***
Firms (1,000 inh.)	-1.886	-2.093	-1.680	-1.727	-1.778	-1.863	-1.382	-1.865	0.169	-1.335	1.446*	0.847
Small firms (%)	0.002	0.001	0.003	0.003	0.000	0.001	-0.003	0.002	-0.006	-0.003	-0.002	-0.005
Construction firms (%)	0.010	0.012	0.004	0.008	-0.008	0.000	-0.010	-0.010	-0.010	-0.009	-0.014***	-0.009
Female mayor	-0.005	-0.001	0.004	-0.004	0.012	-0.003	0.029	0.012	0.021	0.038	-0.003	0.018
Graduated mayor	-0.052	-0.063	-0.025	-0.046	0.010	-0.025	0.029	0.023	0.034	0.013	0.038	0.037
Incumbent mayor	-0.076	-0.057	-0.074	-0.086	-0.088	-0.058	-0.091	-0.106	-0.067	-0.097	-0.025	-0.066

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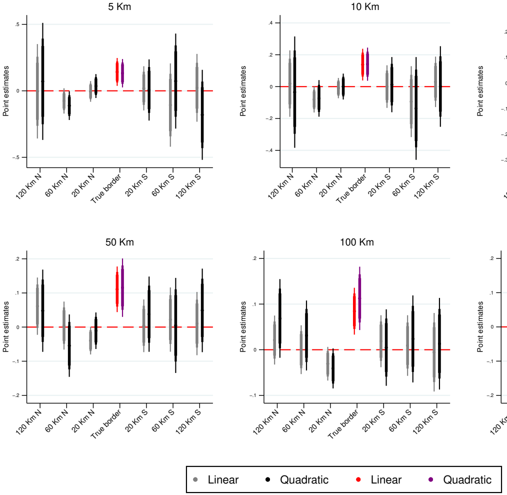
Placebo: Diff-in-Disc



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Robust Coefficient: Diff-in-Disc

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.
Treat X Post 2006	0.132***	0.135***	0.141***	0.139***	0.138***	0.142***	0.115***	0.130***	0.112***	0.125***	0.083***	0.096***
	(0.041)	(0.041)	(0.040)	(0.040)	(0.037)	(0.039)	(0.033)	(0.037)	(0.027)	(0.032)	(0.017)	(0.022)
Observations	1,298	1,298	2,023	2,023	3,934	3,934	7,105	7,105	10,904	10,904	17,111	17,111
R-squared	0.706	0.708	0.700	0.702	0.724	0.724	0.784	0.784	0.823	0.823	0.806	0.806
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.0887	.0967	.0648	.0702	.0502	.0505	.0453	.0468	.0455	.0458	.0495	.0499
Bootstrap	.0018	.0013	.001	.0011	.0004	.0004	.0009	.001	.0001	.0002	0	0
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.17	.17	.15	.15	.12	.12	.11	.11	.11	.11	.1	.1

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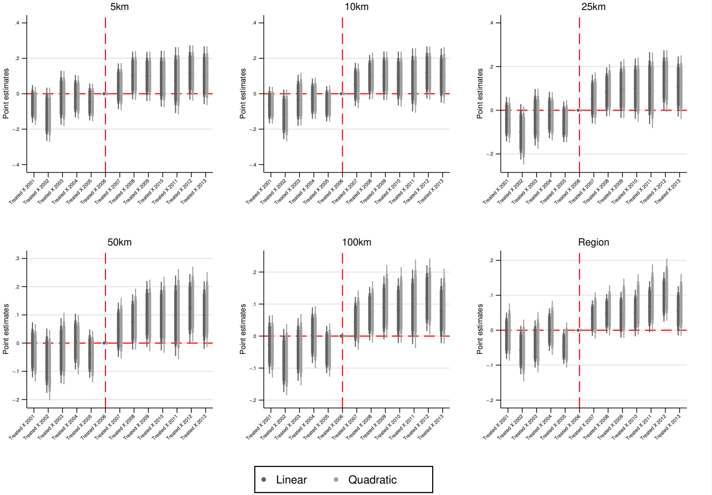
Robust Coefficient: Event Study



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Random Seeds

	(1) Inf.	(2) Inf.	(3) Inf.	(4) Inf.	(5) Inf.	(6) Inf.	(7) Inf.	(8) Inf.	(9) Inf.	(10) Inf.	(11) Inf.	(12) Inf.
Treat X Post 2006	0.102***	0.093**	0.099***	0.101***	0.089***	0.099***	0.084***	0.086***	0.065***	0.086***	0.050***	0.065***
	(0.037)	(0.038)	(0.036)	(0.037)	(0.031)	(0.035)	(0.024)	(0.031)	(0.018)	(0.025)	(0.011)	(0.016)
Observations	1,298	1,298	2,023	2,023	3,934	3,934	7,105	7,105	10,904	10,904	17,111	17,111
R-squared	0.745	0.748	0.751	0.751	0.786	0.786	0.842	0.842	0.873	0.874	0.863	0.863
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.0709	.0831	.0616	.0618	.0578	.059	.0619	.062	.0663	.0676	.075	.0757
Bootstrap	.0073	.0142	.0072	.0091	.0045	.0054	.0006	.0064	.0004	.0008	0	0
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.16	.16	.14	.14	.1	.1	.1	.1	.1	.1	.09	.09

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Placebo: Diff-in-Disc with Sardinia

	(1)
	Inf.
Treat X Post 2006	-0.031***
	(0.006)
Observations	9,501
R-squared	0.563
Within R-squared	.0173
Bootstrap	0
Mun. FE	YES
Year FE	YES
Base value 2006	.08

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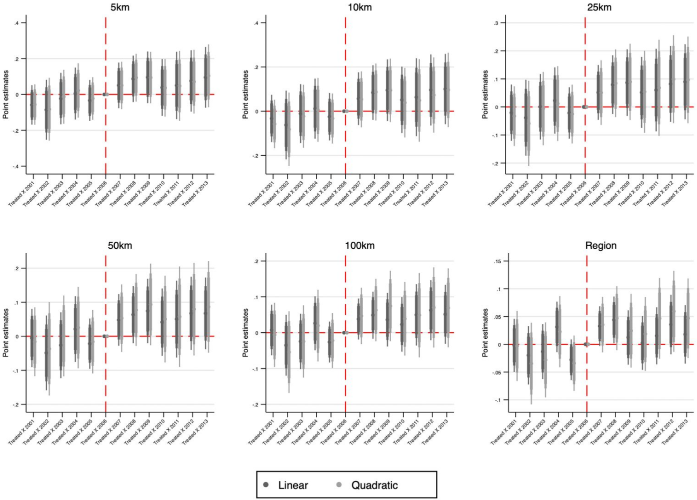
Removing Capital Spending from the Prediction



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Removing 2007-2013 from the Training

	(1) Inf.	(2) Inf.	(3) Inf.	(4) Inf.	(5) Inf.	(6) Inf.	(7) Inf.	(8) Inf.	(9) Inf.	(10) Inf.	(11) Inf.	(12) Inf.
Treat X Post 2006	0.094**	0.082**	0.097**	0.093**	0.079**	0.096**	0.060**	0.076**	0.035*	0.061**	0.002	0.020
	(0.039)	(0.040)	(0.038)	(0.039)	(0.033)	(0.037)	(0.026)	(0.033)	(0.020)	(0.027)	(0.013)	(0.017)
Observations	1,298	1,298	2,023	2,023	3,926	3,926	7,042	7,042	10,791	10,791	16,991	16,991
R-squared	0.551	0.557	0.543	0.544	0.573	0.574	0.662	0.663	0.717	0.717	0.710	0.710
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.0492	.0632	.0479	.0496	.0397	.0419	.036	.0371	.0368	.0386	.0339	.0345
Bootstrap	.0176	.0443	.0115	.0186	.0168	.011	.0225	.0219	.0815	.0274	.9027	.2449
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.12	.12	.1	.1	.08	.08	.07	.07	.06	.06	.05	.05

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Mafia-Related Crimes: Diff-in-Disc

	(1) Mafia	(2) Mafia	(3) Mafia	(4) Mafia	(5) Mafia	(6) Mafia	(7) Mafia	(8) Mafia	(9) Mafia	(10) Mafia	(11) Mafia	(12) Mafia
Treat X 2007 - 2008	0.502	0.396	0.548	0.559	0.137	0.364	0.072	0.209	0.224	0.013	0.075	0.112
	(0.463)	(0.486)	(0.520)	(0.470)	(0.550)	(0.541)	(0.487)	(0.556)	(0.374)	(0.500)	(0.243)	(0.334)
Treat X 2009 - 2012	1.327**	1.212*	1.281**	1.351**	0.950*	1.150*	0.959**	0.945*	1.040***	0.940**	0.697***	0.984***
	(0.625)	(0.665)	(0.620)	(0.627)	(0.552)	(0.617)	(0.426)	(0.552)	(0.320)	(0.443)	(0.194)	(0.270)
Observations	1,198	1,198	1,867	1,867	3,630	3,630	6,567	6,567	10,072	10,072	15,795	15,795
R-squared	0.476	0.479	0.459	0.461	0.425	0.426	0.425	0.426	0.448	0.449	0.460	0.461
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.2484	.252	.2368	.2398	.2147	.216	.2184	.22	.2411	.2418	.2506	.2519
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	2.14	2.14	2.14	2.14	2.21	2.21	2.33	2.33	2.09	2.09	1.84	1.84

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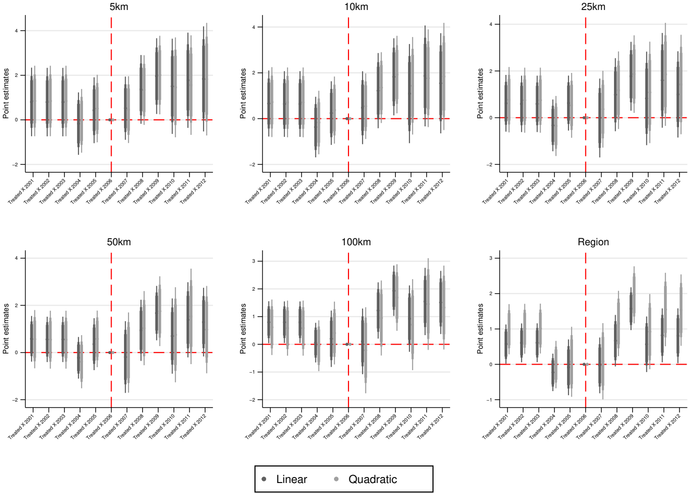
Mafia-Related Crimes: Event Study



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Mafia-Related Crimes: Diff-in-Disc - 2 Post Periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia	Mafia
Treat X 2007 - 2008	0.502	0.396	0.548	0.559	0.137	0.364	0.072	0.209	0.224	0.013	0.075	0.112
	(0.463)	(0.486)	(0.520)	(0.470)	(0.550)	(0.541)	(0.487)	(0.556)	(0.374)	(0.500)	(0.243)	(0.334)
Treat X 2009 - 2012	1.327**	1.212*	1.281**	1.351**	0.950*	1.150*	0.959**	0.945*	1.040***	0.940**	0.697***	0.984***
	(0.625)	(0.665)	(0.620)	(0.627)	(0.552)	(0.617)	(0.426)	(0.552)	(0.320)	(0.443)	(0.194)	(0.270)
Observations	1,198	1,198	1,867	1,867	3,630	3,630	6,567	6,567	10,072	10,072	15,795	15,795
R-squared	0.476	0.479	0.459	0.461	0.425	0.426	0.425	0.426	0.448	0.449	0.460	0.461
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.2484	.252	.2368	.2398	.2147	.216	.2184	.22	.2411	.2418	.2506	.2519
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	2.14	2.14	2.14	2.14	2.21	2.21	2.33	2.33	2.09	2.09	1.84	1.84

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Only Decentralization: Lazio Vs Campania

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.	Inf.
Treat X Post 2006	0.124	0.094	0.127	0.128	0.074	0.118	0.043	0.057	-0.002	0.051	0.018	-0.026
	(0.109)	(0.097)	(0.110)	(0.109)	(0.087)	(0.107)	(0.055)	(0.085)	(0.032)	(0.054)	(0.018)	(0.032)
Observations	273	273	491	491	1,137	1,137	2,793	2,793	7,323	7,323	12,002	12,002
R-squared	0.786	0.798	0.800	0.801	0.839	0.841	0.872	0.872	0.862	0.862	0.835	0.836
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.0981	.1462	.0782	.0827	.0458	.0546	.0462	.0466	.0409	.0433	.0434	.0449
Bootstrap	.256	.3364	.2692	.242	.4418	.3097	.4654	.5645	.9368	.3714	.3138	.4222
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.06	.06	.08	.08	.07	.07	.09	.09	.1	.1	.09	.09

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Decentralization + Increase funding: Puglia Vs Molise

	(1) Inf.	(2) Inf.	(3) Inf.	(4) Inf.	(5) Inf.	(6) Inf.	(7) Inf.	(8) Inf.	(9) Inf.	(10) Inf.	(11) Inf.	(12) Inf.
Treat X Post 2006	0.184***	0.192***	0.198***	0.188***	0.187***	0.212***	0.142***	0.181***	0.087**	0.146***	0.093***	0.119***
	(0.057)	(0.059)	(0.053)	(0.056)	(0.047)	(0.052)	(0.041)	(0.047)	(0.036)	(0.043)	(0.029)	(0.037)
Observations	324	324	506	506	1,078	1,078	1,920	1,920	2,658	2,658	5,109	5,109
R-squared	0.465	0.469	0.477	0.478	0.496	0.498	0.505	0.510	0.537	0.541	0.538	0.539
Poly.	1st	2nd	1st	2nd	1st	2nd	1st	2nd	2nd	2nd	1st	2nd
Specification	5Km	5Km	10Km	10Km	25Km	25Km	50Km	50Km	100Km	100Km	Regions	Regions
Within R-squared	.137	.1426	.1242	.1268	.0828	.0873	.042	.0518	.0362	.0437	.0794	.0818
Bootstrap	.0033	.003	.0005	.0037	.0001	0	.0014	.0006	.0232	.0023	.0009	.0023
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	.32	.32	.26	.26	.17	.17	.13	.13	.12	.12	.12	.12

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