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Mafia, Politics & Machine Predictions

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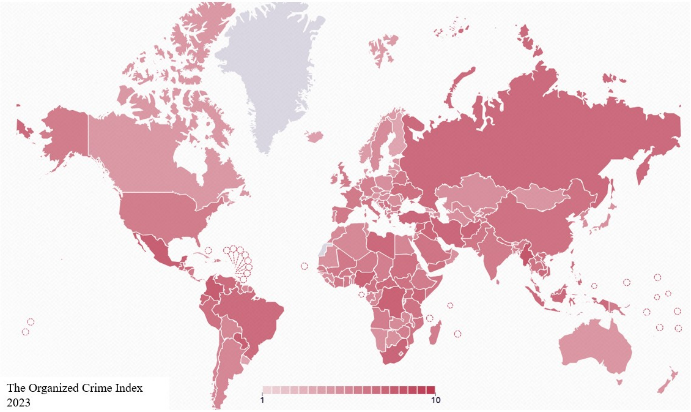
- 80% of the global population lives in countries where organized crime (OC) presents a high risk [Organized Crime Index, 2023], with negative effects on society, e.g. economic growth, human capital, influence on **politics** [Alesina et al., 2019; Daniele and Dipoppa, 2017; Pinotti, 2015b; Sviatschi,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



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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
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  - 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 risk measure to improve the detection of mafia infiltration in local politics
- A stronger state presence... Do redistributive policies discourage or promote OC influence on local politics?
  - Transfers foster economic growth, reducing the grip of OC
  - Transfers attract OC to new areas

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

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  - Does a redistributive policy targeting areas affected by OC (the 2007-2013 EU funds transfers) reduce mafia infiltration in politics? **NO, it increases it.**

Literature

- Origins and migration of OC [Acemoglu et al., 2020; Buonanno et al., 2015; Dimico et al., 2017; Dipoppa, 2021; Varese, 2001]

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- Anti-OC policy:
  - City councils dismissals for mafia [Acconcia et al., 2014; Daniele and Geys, 2015; Fenizia, 2018; Galletta, 2017]
  - Unintended effects of anti-OC policies [Battiston et al., 2022; Castillo and Kronick, 2020; Daniele and Dipoppa, 2023; Dell, 2015; Lessing, 2017]

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  - Unintended effects of anti-OC policies [Battiston et al., 2022; Castillo and Kronick, 2020; Daniele and Dipoppa, 2023; Dell, 2015; Lessing, 2017]
- Redistributive policy (EU funds) and economic development [Alesina and Perotti, 2002; Becker et al., 2010a]
- 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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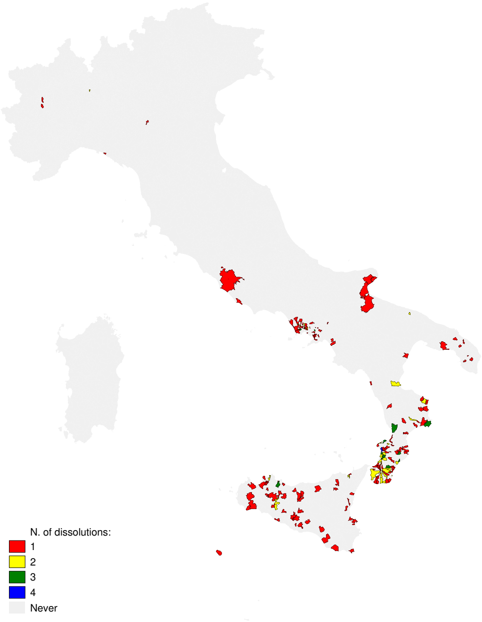
After the dismissal, three appointed bureaucrats rule the municipality up to 24 months

Most of the 379 dismissals took place in three Southern regions: Calabria, Campania and Sicily

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
  - 0 otherwise ▸ Dissolved Councils and Infiltration distribution over time

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- Nine algorithmic approaches (LR, Lasso, Ridge, Elastic Net, DT, RF, GBoosting, XGBoost, DNN)
  - Optimization via Hyperparameter Grid Search (1500+ model candidates, 200 tested)
  - Run-time: 20 hours on 8-core machine, $\sim$ 5 hours on 32-core cluster

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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
- We chose to maximize true positives (i.e., penalize false negatives)

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{1}$$

- Alternative metric: Precision

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

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 $\longrightarrow$ 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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- 200+ variables per each observation
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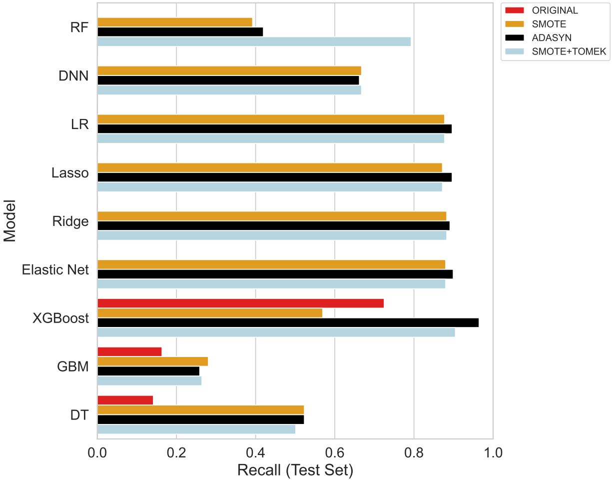
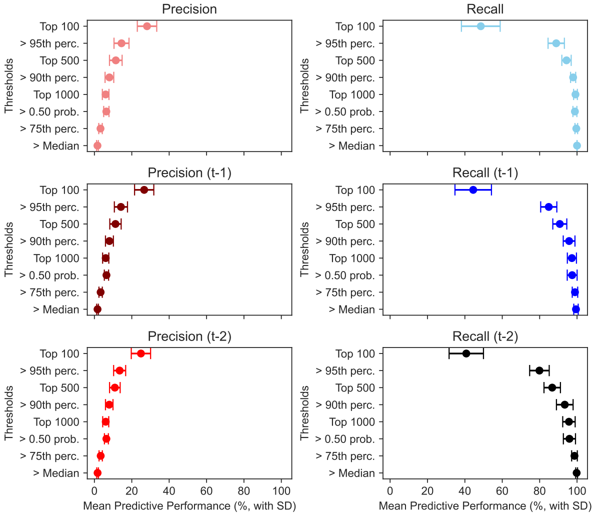
  - 22 Public Spending variables (at t and t-1), e.g. Local Police, Education, Environment, Health, Tourism
  - We differentiate across different versions of the spending variables (e.g. current and capital spending) Details

Prediction Performance: Recall



Revoked Vs Confirmed dismissals

Recall and Precision for Various Rankings, by Year



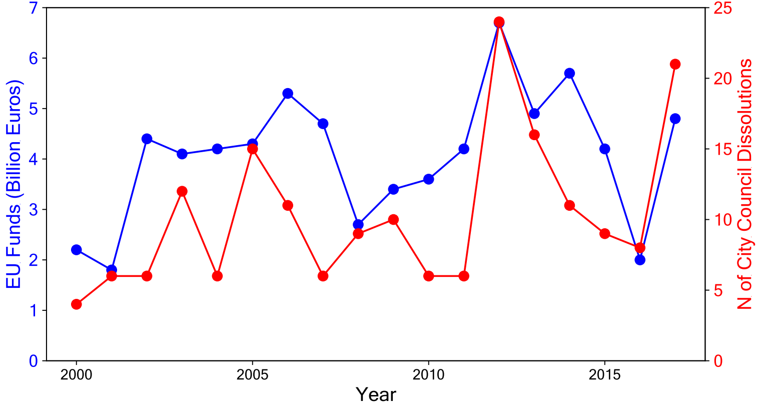
▸ By macro-regions ▸ Where we contribute

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

Part II: Redistributive policy and on mafia infiltration in politics

A stronger State presence



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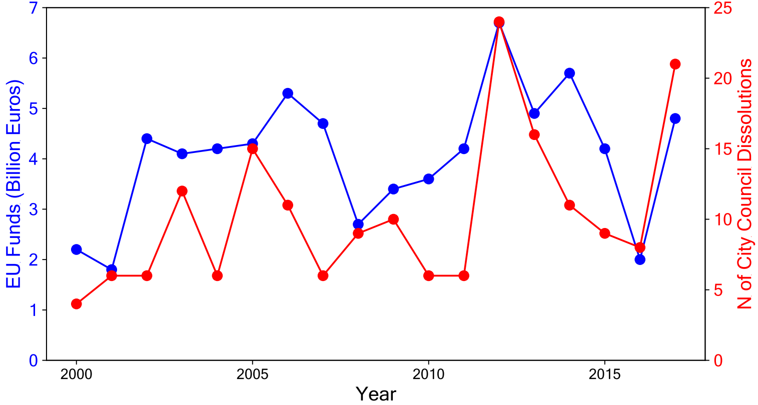

- Do redistributive policy reduce or foster mafia infiltration in politics?
  - Transfers can foster economic growth, reducing the grip of mafia, or they might push mafia towards local governments managing new funds
- Why do transfers promote growth in some areas and not in others?
  - Becker et al [2010b] 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
- Budget increase from about 30 to 56 billion Euros

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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

$$\begin{aligned} \text{Infiltration}_{i,t} = {} & \alpha + \beta \text{Treated}_i \times \text{Post2006}_t + \eta f(\text{Distance}_i) \times \text{Post2006}_t \\ & + \gamma \text{Treated}_i \times f(\text{Distance}_i) \times \text{Post2006}_t + FE_i + FE_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

- 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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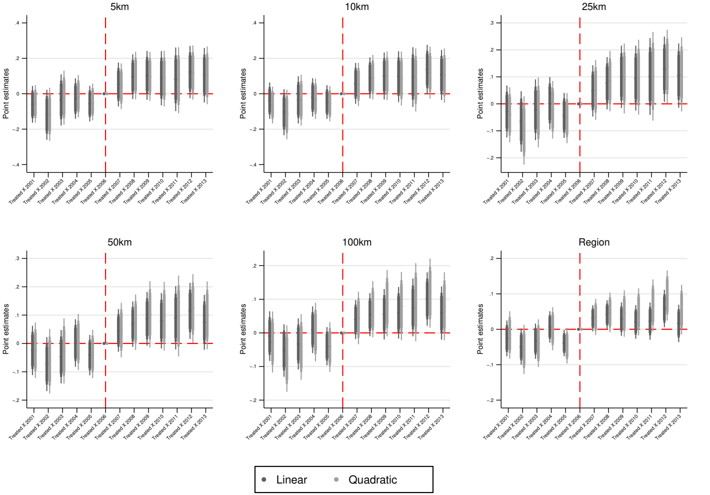
- Changes in covariates induced by the treatment balance between T and C

▸ 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



Graphical Evidence

Additional Tests

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

Conclusions

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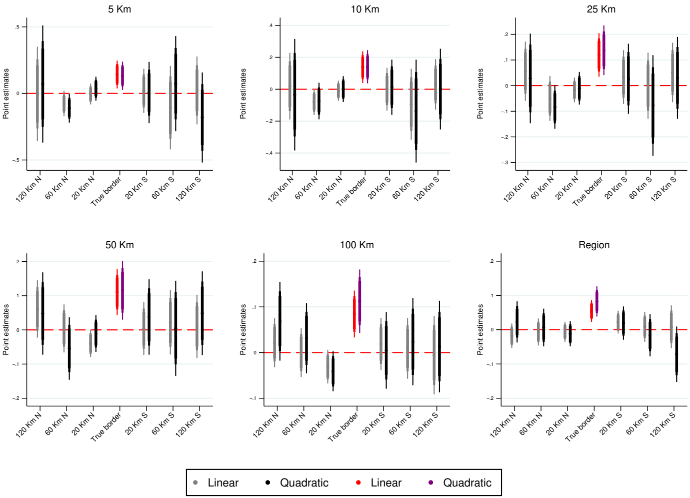
- The 2007-2013 wave of EU funds increased the risk of mafia infiltration in treated municipalities
- The mix of predictive and causal methods offers insights into the effects of increased state presence (transfers) in OC affected areas

> Thanks for attending!

Questions? Comments?

Appendix.

Placebo: Diff-in-Disc



Back

Robust Coefficient: Diff-in-Disc

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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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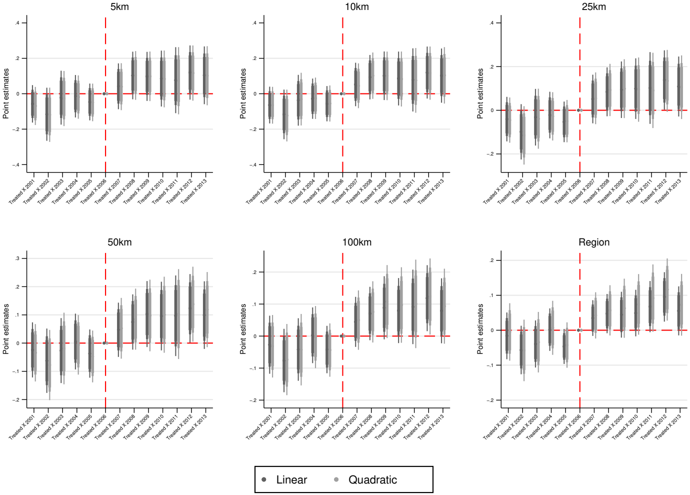
Robust Coefficient: Event Study



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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)	(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	0.184***	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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Alternative Algorithm: 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	0.067**	0.071**	0.060**	0.067**	0.039*	0.056**	0.048**	0.039	0.038**	0.048**	0.027***	0.039***
	(0.031)	(0.032)	(0.029)	(0.031)	(0.024)	(0.028)	(0.019)	(0.024)	(0.015)	(0.020)	(0.010)	(0.013)
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	0.730	0.730	0.730	0.731	0.745	0.747	0.800	0.800	0.830	0.830	0.819	0.819
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	.0341	.0352	.0256	.0279	.019	.0244	.0216	.0222	.02	.0202	.0233	.0237
Bootstrap	.0316	.0314	.0368	.0291	.1046	.048	.0109	.1115	.012	.0157	.0057	.003
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	.08	.08	.07	.07	.06	.06	.06	.06	.07	.07	.07	.07

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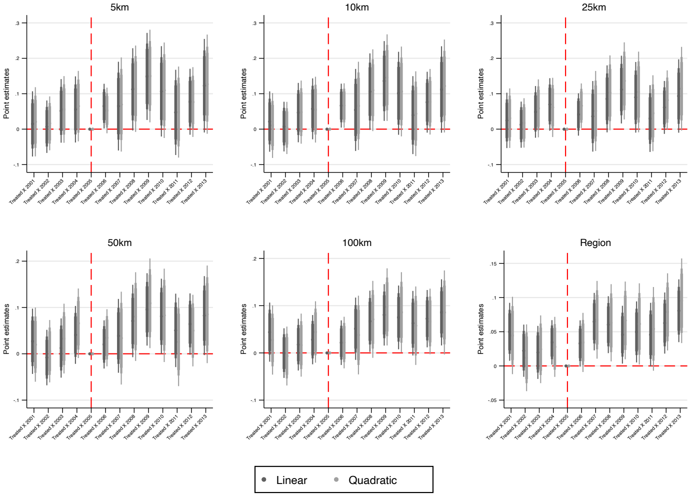
Alternative Algorithm: Event Study



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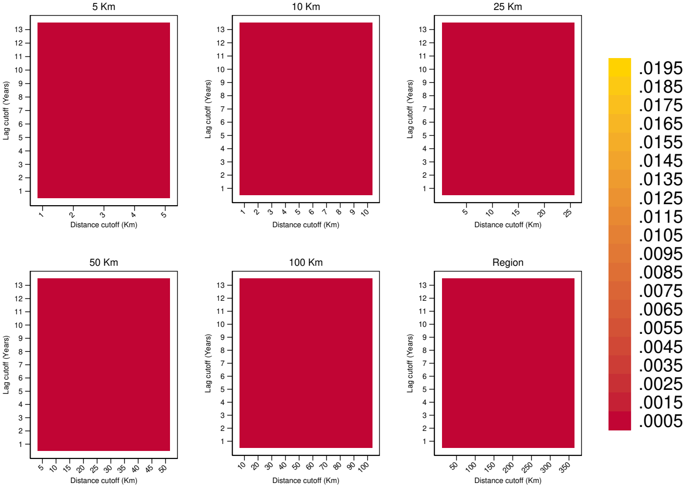
Conley HAC Standard Errors: Diff-in-Disc



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Mafia-Related Crimes: Diff-in-Disc

	(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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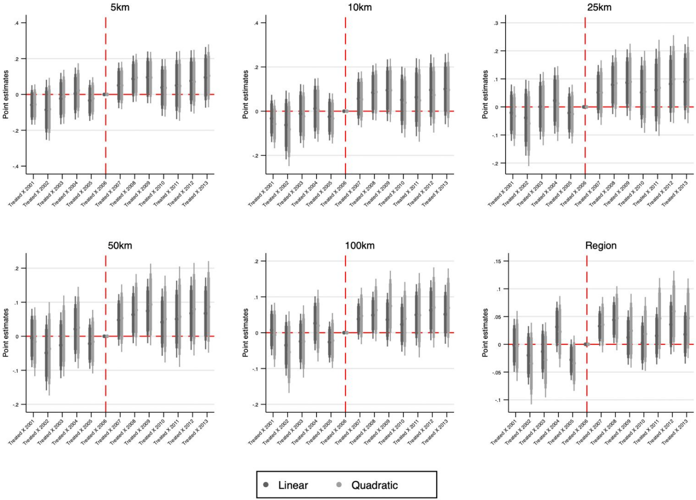
Removing Capital Spending from the Prediction



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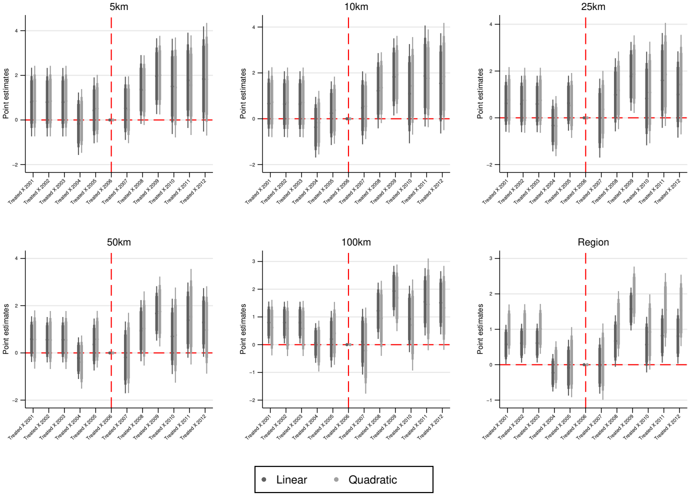
Mafia-Related Crimes: Event Study



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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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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.

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.

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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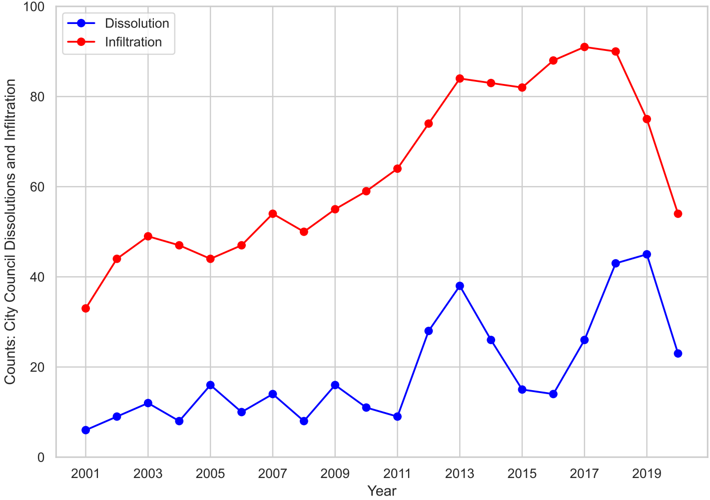
Dissolved Councils and Infiltration distribution over time



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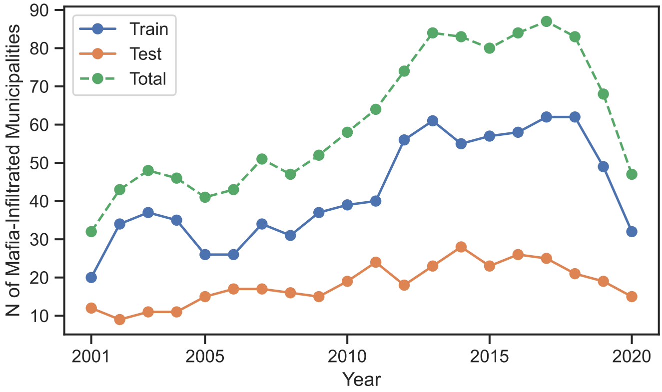
Infiltration distribution over time



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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)

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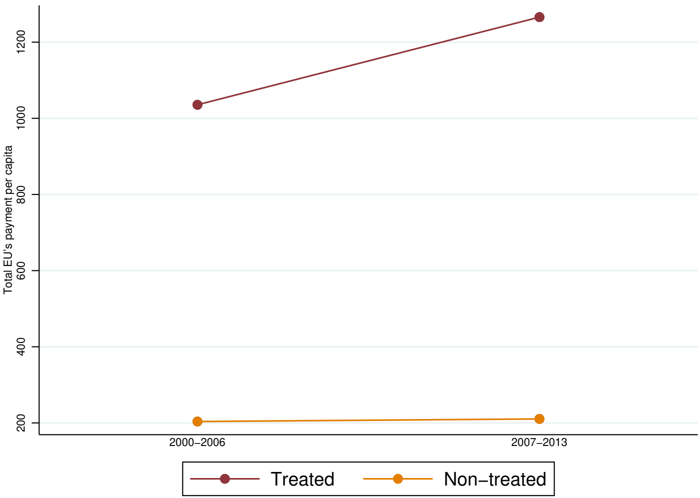
Dynamics of EU Funds



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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

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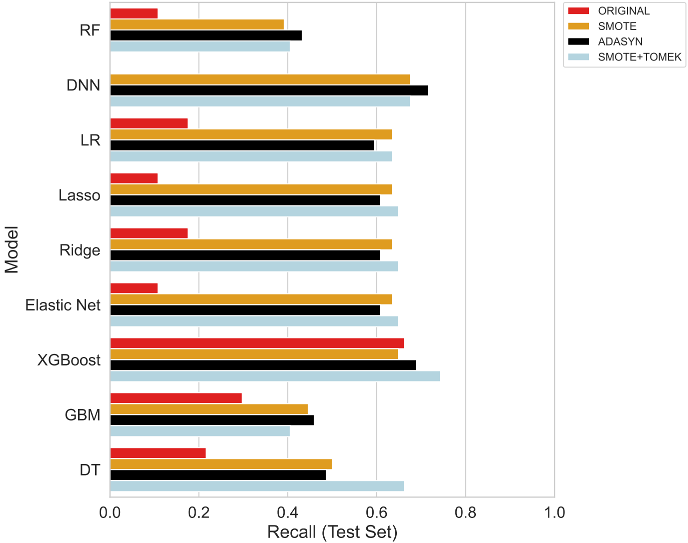
Predictive Performance



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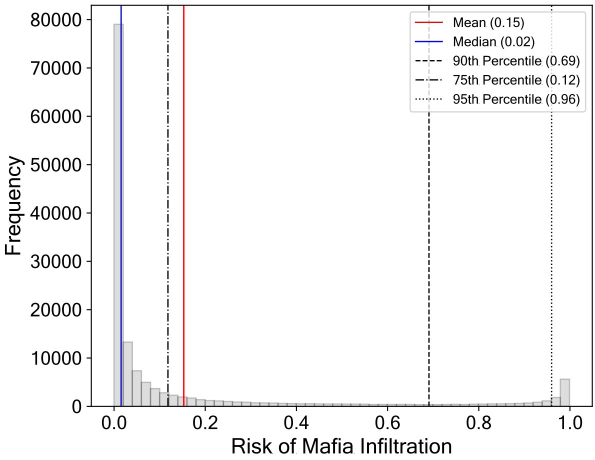
Predicted Infiltration Risk 2001-2020, Distribution



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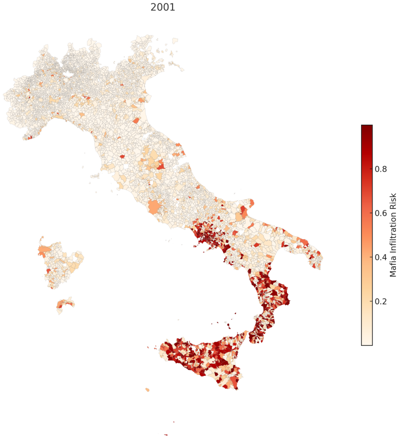
Predicted Infiltration Risk 2001-2020, Distribution in Time and Space



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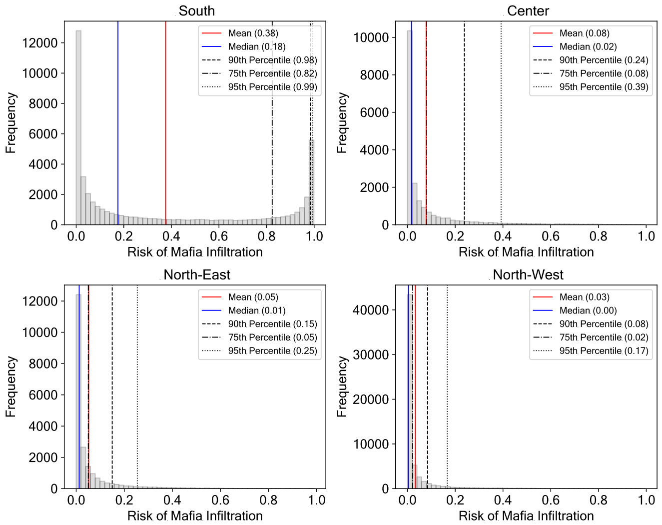
Predicted Infiltration Risk 2001-2020, Distribution (by Macro-Region)



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Public Spending Variables/2

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

- Share of *current* expenses

$$\text{Share Curr. } (x)_{i,t} = \frac{\text{Curr}(x)_{i,t}}{\sum_{x \in X} \text{Curr}(x)_{i,t}} \tag{4}$$

- Share of *capital* expenses

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

- Expense rate

$$\text{Rate}(x)_{i,t} = \left(\frac{\text{Curr}(x)_{i,t} + \text{Cap}(x)_{i,t}}{\text{pop}_{i,t}} \right) \times 10k \tag{6}$$

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

$$\text{Share Curr. Global } (x)_{i,t} = \frac{\text{Curr}(x)_{i,t}}{\sum_{x \in X} (\text{Curr}(x)_{i,t} + \text{Cap}(x)_{i,t})} \tag{7}$$

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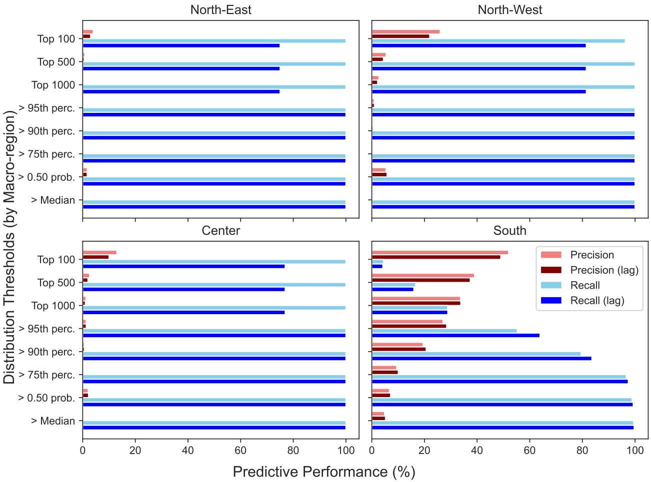
Recall and Precision for Various Rankings, by Macro-Region



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Investigations step

- We can improve the first steps of the detection process, i.e. the probability to start an investigation ("proactive" instead of "reactive" investigations)

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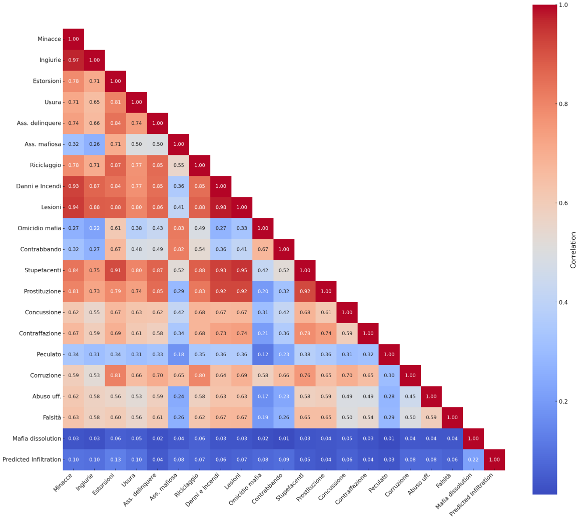
Predicted Infiltration Risk 2001-2020, Correlations



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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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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%

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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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	-0.618**	-0.593**	-0.597**	-0.616**	-0.605***	-0.622***	-0.511***	-0.648***	-0.077	-0.549***	0.352***	0.351***
Household size	-0.034	-0.034	-0.014	-0.031	-0.003	-0.010	-0.006	-0.014	0.056*	-0.020	0.206***	0.143***
Aging rate	7.095	2.772	0.837	5.847	0.568	0.362	-5.282	4.610	-40.932***	-4.181	-72.433***	-65.122***
Poor families	0.155	0.066	0.353	0.151	0.445	0.377	0.209	0.391	1.189***	-0.024	2.851***	2.531***
College rate (30-34)	-1.981*	-2.341**	-1.666*	-1.969*	-0.740	-1.429	-0.403	-0.668	-0.550	-0.534	-0.011	-0.682
Dropout rate	3.231*	3.148*	3.844**	3.221*	3.155**	3.795**	3.311***	3.042**	4.023***	3.537***	4.404***	4.582***
Unemployment rate	0.430	0.471	0.651	0.381	1.098	0.885	0.969	1.011	3.282***	0.432	6.072***	6.012***
Firms (1,000 inh.)	-7.105**	-8.385**	-6.425*	-6.437*	-5.792**	-6.818**	-4.088*	-6.183**	-4.685**	-2.853	-2.704*	-7.325***
Small firms (%)	0.025	0.024	0.025*	0.023	0.029**	0.028*	0.024**	0.030**	0.014*	0.024**	0.000	0.006
Construction firms (%)	-0.016	-0.012	-0.020	-0.016	-0.010	-0.019	-0.019*	-0.010	-0.015*	-0.020*	-0.016**	-0.016*
Female mayor	0.000	0.002	0.000	0.001	0.003	0.006	-0.009	0.004	-0.008	-0.017	0.005	-0.016
Graduated mayor	-0.036	-0.028	-0.043	-0.042	0.041	-0.024	0.116	0.022	0.139**	0.119	0.165***	0.154***
Incumbent mayor	0.096	0.102	0.071	0.095	0.033	0.059	0.025	0.042	0.016	0.031	-0.005	0.009

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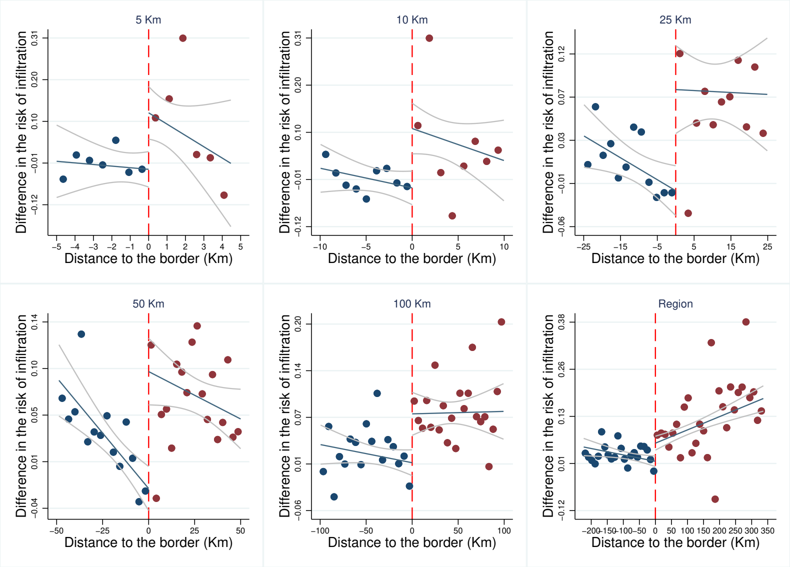
Results: Graphical Evidence



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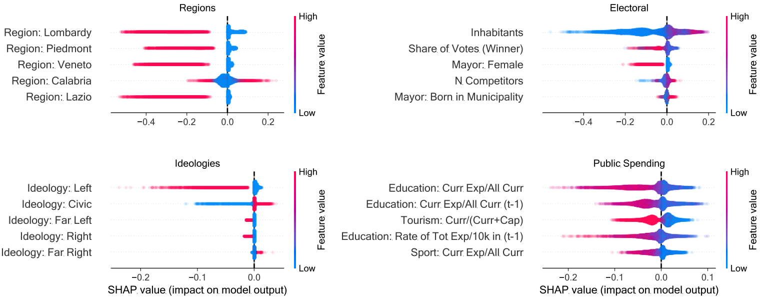
SHAP: Explainability Results



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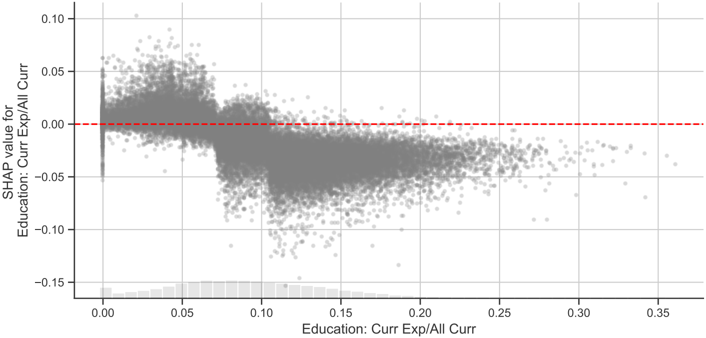
Feature Explainability - Example



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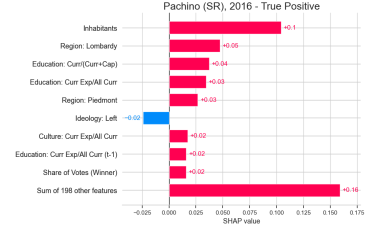
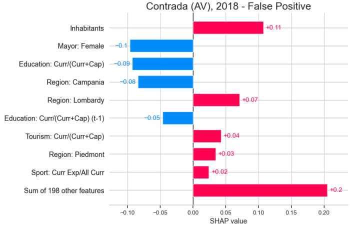
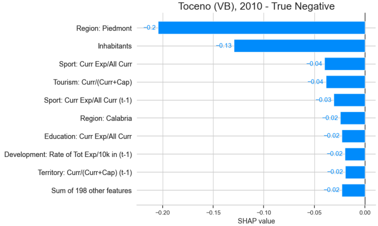
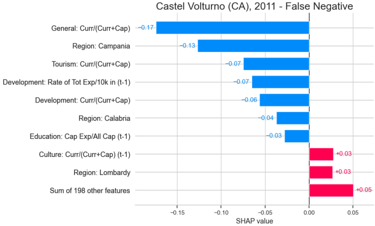
Locally Explainable Predictions









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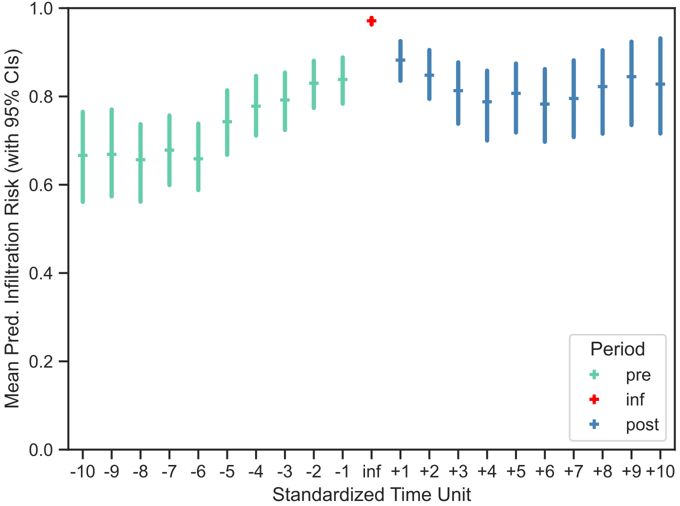
Descriptive Evidence: Predicted Infiltration Risk for Dissolved Municipalities



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