Mafia infiltrations in Italian municipalities: two statistical indicators

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Abstract

We study the administrative behaviour of a sample of Italian municipalities dismissed by the Government because of mafia infiltrations, looking at their balance-sheet data. Using linear discriminant analysis and logistic regressions, we put forward two statistical indicators of the probability that a mafia infiltrated a city council. Our results characterise the administrative profile of infiltrated municipalities. We obtain non-obvious results concerning their i) high levels of arrears, both of tax collections and payments; ii) low levels of indebtness; and iii) low levels of capital expenditures, especially for public works.

JEL classification: D73, H7, H83, P48.

Keywords: Mafia infiltration, Organised Crime, Local authorities.

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1 Introduction and motivation

The existence of large and powerful criminal organisations is a worldwide phenomenon that affects the life of people and the functioning of political institutions in many advanced and developing countries.¹ The presence of

 $^{^1\}mathrm{Most}$ notably in countries like Italy, Japan, U.S.A., China, Columbia, Russia, Mexico, among others.

organised crime (henceforth OC) has detrimental effects on economic growth (Pinotti 2015, Shleifer and Vishny 1993, Acemoglu et al. 2020), on the functioning of competitive markets (Slutzky and Zeume 2020, Calamunci and Drago 2020), on the quality of national and local political institutions (Daniele and Geys 2015, van Dijk 2007) and on the level of political corruption (Gounev and Bezlov 2010, Buscaglia and van Dijk 2003). The determinants of the emergence of such organizations appear to be related to the history and the socio-political conditions of a country or of a region (Bandiera 2003, Acemoglu et al. 2020, Buonanno et al. 2012, Dimico et al. 2017). The collusion with political actors and the weakness of law enforcement is one of the causes of the rise and success of large criminal organizations.

The attempt to influence and control political institutions, both at national and local level, is a pivotal element of the modus operandi of OC. Indeed, the flows of public expenditure (especially the investments in infrastructures and the provision of healthcare services²), as well as public funding to private businesses, provide lucrative opportunities for criminal organizations (Gounev and Bezlov 2010, Jonhson 2020, Barone and Narciso 2015). OC pursues the capture of politicians through a mixture of bribery, intimidation and violence—the 'plata o plomo' approach—along with the infiltration (in a strict sense) of their members in elected political bodies and/or in the administrative staff of national, regional and local authorities (Alesina et al. 2016, Acemoglu et al. 2013, Dal Bò et al 2006). This problem is particularly felt in Italy, where four large criminal organizations are present: Mafia, Camorra, 'Ndrangheta and 'Sacra Corona Unita'. To tackle the interference and pressure of these criminal organizations on local authorities, in 1991 the Italian legislator passed a law that gives to the Government the power to dismiss a city council if there is sufficient evidence of being under the influence or control of a mafia.⁴ Since then, three hundred and eighteen city councils have been dismissed and put under commissionership.⁵ The dismissal

²This problem is particularly severe in Italy where, between 2006 and 2019, the Government has dismissed six Local Health Care authorities, four in Calabria and two in Campania, because of Mafia infiltrations and control. Johnson (2020) provides a detailed description of this issue.

³These organizations are based, respectively, in Sicily, Campania, Calabria and Apulia, although their activities extend well beyond the boundaries of these four southern Italian regions. Henceforth we will generically refer to these organizations as 'mafia'.

⁴Decreto Legge 164/1991, subsequently Art. 143 of the 'Testo Unico sugli Enti Locali', "Scioglimento dei consigli comunali e provinciali conseguente a fenomeni di infiltrazione e di condizionamento di tipo mafioso o similare. Responsabilità dei dirigenti e dipendenti". Occhiuzzi (2019) provides an analysis of the legal aspects of this law and of its application.

⁵More precisely, up to March 2020 we had 531 decrees of dismissal, 187 of which apply to city councils that have been previously dismissed. 26 out of 531 dismissals have

procedure starts with police investigations that are usually triggered by a variety of signals, such as: i) links, frequentations and relationships between administrators and members of a mafia; ii) crimes committed by administrators; iii) acts of intimidation against administrators and other public officers; iv) electoral disturbances; v) administrative irregularities; and, naturally, vi) mafia related murders and crimes. Upon the reception of the police reports that indicate a potential case of infiltration, the 'Prefetto' – i.e., the local representative of the national government – appoints a committee that includes officers from the 'Prefettura' (the cabinet of the 'Prefetto') and officers from the three Italian police corps (State Police, Carabinieri and 'Guardia di Finanza'). The committee investigates the case and writes a report that is then used by the Ministry of Interior for the final decision. The eventual order of dismissal, sanctioned by a decree signed by the President of the Republic, establishes the commissionership of the institution for a period of twelve to eighteen months. This period of commissionership, that can be extended to twenty-four months, serves the purpose of carrying on the ordinary acts of administration while organizing new elections.

A crucial step in the repression of the phenomenon at hand is the identification of local authorities fallen under the influence of a mafia. Is there a recurrent pattern in the administrative behaviour of the municipalities infiltrated by a mafia? If so, can we obtain from the accounting data of municipalities some 'red flags' that can help to detect these infiltrations? We address these questions performing a statistical exercise aiming at discriminating between infiltrated and non-infiltrated city councils. Most of the dismissed municipalities, 93%, are located in Campania, Calabria, Sicily and Apulia. We take a sample composed of fifty-seven of these city councils, the ones dismissed between July 2010 and August 2016, and study their balance-sheet data looking for regularities that characterise the administrative behaviour of these local authorities infiltrated by a mafia.

The statistical analysis presented below uses two known methods, namely multivariate Linear Discriminant Analysis (henceforth LDA) and logistic regressions, to assess the likelihood of mafia infiltrations. In both approaches, we complement our sample of dismissed municipalities with a sample of one hundred well-administered ones, chosen to mimic the dimensional distribution of the former. Applying the LDA to some headings and ratios of the balance sheets of these city councils, we obtain a classifier that discriminates between 'healthy' and 'corrupt' local authorities. We call this classifier the 'Mafia Infiltration Warning Indicator' (henceforth MIWI). Similarly, we run logistic regressions on balance-sheet data to obtain logistic models that es-

subsequently been withdrawn by regional administrative courts.

timate the probability that a mafia has infiltrated a given local authority. We call these models 'Mafia Infiltration Probability' indicators (henceforth MIP). Both these statistical exercises deliver results that appear accurate and reliable. These results neatly depict a distinct administrative profile for our sample of infiltrated municipalities.

A recent and growing stream of literature, briefly discussed in the next section, studies the consequences of the influence of mafia on Italian polity and economy. The present paper contributes to this literature with a focus and a statistical method that differ from the other works. To the best of our knowledge, we are the first who aim at discriminating between infiltrated and non-infiltrated municipalities, looking for detectable regularities in the balance-sheet data of the former, and identify a distinctive administrative profile of such municipalities. Moreover, in so doing we obtain neat and non-obvious results concerning i) capital expenditures, ii) levels of indebtness and of dependence on Government transfers, and iii) arrears in tax collection and payments of the municipalities fallen under the control of mafia.

The paper is organised as follows. The next section presents the literature related to the present work. Section 3 presents the two samples of city councils and the set of variables and ratios, taken from their balance-sheets, that we use in our empirical investigation. Section 4 presents the results obtained by applying the LDA and the logistic regressions to the abovementioned set of balance sheet data, along with the results of validation tests run a set of municipalities dismissed between September 2016 and November 2017. Finally, the conclusions are drawn in Section 5.

2 Related literature

During the last decade appeared several works investigating the effects that the presence of strong mafia organisations have on Italian political institutions and on the economic performance of Italian firms and territories. Alesina et al. (2019) show that there is an increase in the number of violent crimes against politicians in the time preceding elections, hindering the electoral results for parties that oppose mafia organisations. They also argue that the attacks perpetrated by Sicilian Mafia reduce the anti-mafia activities undertaken by members of the Italian parliament. Pinotti (2015) applies a synthetic control method to estimate the effects that the presence of organised crime had on economic growth in southern Italy during the post-war period. His estimated counterfactual data show that, in the absence of mafia, southern Italian regions would have achieved circa a 16% higher per-capita GDP during the three decades starting from 1980.

Calamunci and Drago (2020) and Slutzky and Zeume (2020) exploit, as a source of data, the staggered enforcement of Italian laws⁶ that enable the Government to confiscate, and put under judicial administration, firms and companies that are proven to belong to a mafia. Calamunci and Drago (2020) use these law enforcement acts to evaluate their effects on the profitability, performance and investments of lawful firms that compete in the same markets as the confiscated ones. Their results show that, during the first four years after the confiscation of a mafia firm, the firms that operate in the same province and in the same industry enjoy higher levels of returns and increase their investments. Along similar lines, Slutzky and Zeume (2020) show that the seizure of mafia firms induces improvements on the competition among firms, the competition in the assignment of public procurement contracts and on the overall level of innovative activities undertaken by firms.

Other authors use the quasi-experiment data furnished by the dismissal of municipalities due to mafia infiltrations, as we do (although for different purposes). Daniele and Geys (2015) show that, after the dismissal of a city council, the average educational level of elected local representatives improves and that the voters tend to shift in favour of younger, female and non-entrepreneurial candidates. Acconcia et al. (2014) note that in the aftermath of the dismissal of a city council, with the consequent commissionership, there is a marked decline in its expenditures; as they put it: 'a sharp, unanticipated and temporary contraction in local public spending. They use this fact to estimate the local output multiplier of cuts in public purchases at a local (provincial) level. They estimate that such multiplier is equal to 1.2 on impact and 1.8 over a two-year period, showing that cuts in local public spending can have considerable effects on the level of local economic activity. Di Cataldo and Mastrorocco (2018) use a difference-in-difference method to estimate the effects of Mafia infiltrations on the allocation of the public resources managed by local authorities between 1991 and 2013. They analyse data on public spending-namely the expenses for municipal police, public lightning, schools, public transports, constructions and waste management expenditures (surprisingly measured together as a single variable)⁷ of the Italian municipalities dismissed because of Mafia infiltration. These authors find that Mafia infiltrations have a statistically significant influence on the sum of constructions and waste management expenditures, which result more abundant in infiltrated municipalities, whereas the expenses for public

⁶The first Italian law to introduce confiscation and judicial administration of firms owned by a mafia is the Law n. 646 of 1982, known as 'Rognoni-La Torre' law.

⁷Constructions, i.e. public works, are accounted for in the 'Titolo Secondo', i.e. capital expenditures, of the balance-sheet of a city, whilst the expenses for waste management belong to the current expenditures, i.e. the 'Titolo Primo'),

transports, local police and education appear smaller than in the other municipalities. Moreover, they find that infiltrated local authorities collect on average fewer waste taxes, a result in line with our findings on tax collection. Cingano and Tonello (2020) find that the dismissal of mafia-infiltrated city councils has no consequences on the number of mafia-related crimes (e.g. homicide, extortion, drug-trafficking and usury). Galletta (2017) finds that, over the period 1998 to 2013, the dismissal of a municipality induces a reduction in public investments in the neighbouring municipalities, an effect due to the perception of tougher law enforcement on the territory. Finally, Fenizia (2018) studies the effects of mafia-related dismissals on the activity of the firms that appear connected with the infiltrated municipalities. She finds a sharp reduction in the probability that those firm win a public procurement contract in the years following the dismissals.

3 The sample and the data

3.1 The sample

The statistical analysis presented below is performed on a sample of 157 Italian municipalities divided into two groups, labelled respectively as "corrupt" and "healthy". The "corrupt" group consists of 57 City Councils dismissed by the Government because of mafia infiltrations in the period ranging from August 2010 and September 2016, apart from the cases in which the dismissal has subsequently been revoked by the judicial authority. Ninety per cent of the municipalities in the corrupt sample is located in Calabria (51%), Sicily (18%) and Campania (21%). The rest is split among the southern region Apulia (3%) and three northern regions, Piedmont (3%), Lombardy (2%) and Emilia-Romagna (2%).

The control group, labelled "healthy", is composed by a set of one hundred well-administered municipalities, taken from Italian regions and provinces selected according to two non-contrasting criteria, namely the quality of the administration and the (low) risk of subjugation to a mafia. Given the target of our exercise—i.e., discriminating between infiltrated and non-infiltrated city councils—and the high secrecy of mafia activities, it is important to contain the risk of having, in the control group, municipalities that are controlled by

⁸The 'healthy' and the 'corrupted' municipalities that compose the samples are listed in Appendix 1.

⁹Among the municipalities dismissed because of mafia infiltrations between 2010 and 2016, the dismissal of the City Council of Bordighera, Ventimiglia, Cirò and Joppolo have been subsequently withdrawn, upon appeal, by the Administrative Court (TAR) of Lazio.

a mafia even if they have not been recognised as such. Indeed, the fact that the Government has not dismissed a city council is not proof of the absence of mafia infiltration. As is known, the Italian mafias not only have a longlasting strong control over the territories of the southern Regions, ¹⁰ in the last two decades they have extended their influence over a number of Provinces located in northern Regions-i.e. in Lombardy, Veneto, Valle d'Aosta, Piedmont and Emilia Romagna-and in central Regions-mostly in Lazio. For these reasons, we took the control sample from Provinces selected on the basis of the Institutional Quality Index (IQI) by Nifo and Vecchione (2014), that ranks the quality of public administration for 107 Italian provinces, 11 and the 'Mafia Index' by Calderoni (2011), an index that we (informally) updated in the light of the mafia-related news and events that occurred in the last ten years. 12 However, a strict application of these two criteria would have yield a sample exclusively composed of Municipalities located in north and central Italy. To obtain a sample more representative of the entire nation including the regions where Mafia, Camorra, 'Ndrangheta and 'Sacra Corona Unita' are based—we choose southern Provinces that, compared to the rest of the respective Region, have a relatively high IQI index and that appear less troubled by the presence of mafia.¹³ At provincial level, the municipalities have been taken in a random fashion stratified by dimension (population), in order to replicate the dimensional distribution of the 'corrupt' group. The so-obtained control sample contains 41 municipalities located in the northern Regions, with a prevalence of Trentino Alto Adige, 33 in the central Regions, with a prevalence of Tuscany, and 26 in the southern Regions. 1415

¹⁰See, inter alia, the 'Mafia index' put forward by Calderoni (2011).

¹¹The Institutional Quality Index (IQI), put forward by Nifo and Vecchione (2014), is a composite indicator built to measure Institutional Quality in Italy. The IQI stems from the World Governance Indicator (WGI). See the website https://sites.google.com/site/institutionalqualityindex/home

¹²For instance, in the last years the small north-western region 'Valle d'Aosta' turned out to be heavily controlled by the Calabrian 'Ndrangheta, whilst the 'Mafia Index' assigned a very low level of mafia presence to this region.

¹³The IQI index assignes scores comprised between 0 and 1, the latter being the highest score. We used scores assigned for the latest available year, i.e. 2012. The central and northern Provinces in our control sample achieve scores in the range 0.7-1. The southern Provinces selected for the control sample achieve scores that range between 0.20 (Cosenza, in Calabria) and 0.53 (Salerno, in Campania).

¹⁴In the Appendix we present the lists of the municipalities that compose the 'corrupt' and the 'healthy' samples, along with their regional distribution.

¹⁵According to the 2019 data presented by ISTAT, the national institute of statistics, 46% of the Italian population lives in the northern Regions, 21% in the central Regions and 33% in southern Regions. With respect to this distribution, our control sample is skewed in favour of central regions, where Provinces located in Tuscany and Marche have

3.2 The balance-sheet data

We investigate the administrative behaviour of our sample of local authorities looking at a number of headings and items of their balance sheets. Our aim is to search for detectable regularities in the management of mafia-infiltrated city councils. Common sense would suggest looking for signs of structural financial weakness: if a mafia influences or controls the management of a local authority, the latter will undertake administrative acts that can be quite costly for the administration, such as over-invoicing, embezzlement, fraud in public works procurement, etc. This plausible conjecture is supported by the facts. Focusing on the three regions where ninety per cent of the municipalities in our 'corrupt' sample are located – Campania, Calabria and Sicily – we see that the incidence of the cases of municipal insolvency occurred between the year 2000 and year 2017 - 103 cases over 1344 municipalities – is equal to 7,6% of all city councils present in these regions. By contrast, this percentage is noticeably larger in our 'corrupt' sample, where we had nine cases of insolvency, over the period 2006-2016, out of our fifty-seven infiltrated municipalities, i.e. the 15,7%. These data support the conjecture that the infiltration of a mafia into a local authority causes a structural financial weakness, exposing the local authority to a high risk of default. Nonetheless, this weakness is not evident in terms of customary financial ratios and appears not detectable through the deficit parameters set by the Government and monitored by the 'Corte dei Conti', the Court that acts as auditor general for the Italian public administration. According to the law, 16 Italian city councils are supposed to comply with ten objective balance-sheet parameters, called 'indicatori di deficitarietà' (deficit indicators). These indicators (labelled D1-D10) are designed to detect cases of a structural deficit of local authorities through the setting of critical thresholds to ten balance-sheet ratios, briefly summarized in the following list:

- D1 current deficit (if any) < 5% of current revenues
- D2 tax revenues arrears accrued in the year < 42% of current revenues
- D3 total amount of tax revenues arrears < 65% of current revenues
- D4 payment arrears < 40% of current expenditures
- D5 payments enforced by Court order < 0.5% of current expenditures
- D6 personnel costs < 38% 40% of current revenues (according to number of inhabitants)
- D7 debt (loans) < 150% (if in surplus) or 120% (if in deficit) of current revenues
 - D8 off-budget debts accrued in the year < 1% of current revenues

some of the highest IQI scores and appear to be free from mafia penetration.

¹⁶Articles 242 and 243 of the 'Testo Unico degli Enti Locali'.

- D9 cash advances from the Treasury < 5% of current revenues
- D10 sales of assets to cover current and past deficits < 5% current expenditures

If a city council fails to meet five or more of the above indicators, the 'Corte dei Conti' officially declares that the administration is in a state of structural deficit. Interestingly, in our sample of infiltrated local authorities, we have nine out of fifty-seven municipalities declared in structural deficit (15,7%) while, over the period 2009-2013, the same occurred to the 21,5% of the municipalities of the three regions at hand.¹⁷ This datum suggests that our infiltrated municipalities pay some attention not to violate the above deficit indicators, probably to avoid the closer monitoring and the administrative limitations consequent to a declaration of a structural deficit. Taking this into account, in our analysis we do not focus merely on measures of financial fragility.

Our prior knowledge of the phenomenon at hand, acquired through the on-field experience of auditing of Italian local authorities and through interviews with commissioners appointed to run city councils dismissed because of mafia infiltrations, ¹⁸ led us to focus our investigation on the following set of variables.

- 1. Tax Revenues Arrears Index (TRAI): Tax Revenue Arrears/Accrued Tax Revenues, the ratio of the above deficit indicator D1. The tax revenue arrears are equal to the difference between the accrued tax revenues, that the city council was supposed to collect, and the amount of taxes that has actually been collected, up to the current year. This sum is weighted with the tax revenues accrued in the year.
- 2. Payment Arrears Index (PAI): Payment Arrears/Accrued Expenditure, the ratio of the above deficit indicator D4. The payment arrears are equal to the difference between the accrued expenses, that the city council was supposed to pay, and the amount of expenses that has actually been paid out, up to the current year. This sum is weighted with the expenditure accrued in the year.
 - 3. Collection of Tax Arrears (CTA): Collected Tax Revenue Arrears/Tax

¹⁷See "Rapporto sull'andamento a livello di aggregati dei parametri di deficitarietà strutturale degli Enti Locali nel periodo 2009-2103", available at the website of the Ministero dell'Interno: https://dait.interno.gov.it/. According to this report, over the period 2009-2013 an average of 11,3% of the Italian municipalities declared in structural deficit have successively become insolvent within the year 2016. In our sample of dismissed municipalities, three were declared to be in structural deficit and successively became insolvent, while the six remaining cases of insolvency recorded in this group of municipalities were not anticipated by a declaration of structural deficit by the 'Corte dei Conti'.

¹⁸Professor Ziruolo is a chartered auditor for Italian public authorities and devotes a substantial part of his time to this activity.

Revenue Arrears. This ratio measures the quota of tax arrears that has been collected during the year.

- 4. Payment of Payment Arrears (PPA): Payment Arrears paid in the year/Payment Arrears. This ratio measures the quota of the payment arrears that have been processed and paid out during the year.
- 5. Debt Index (DI): Passive Interests/Current Revenues. This ratio measures the quota of revenues that a municipality spends on interests accruing on its debts. This ratio is particularly relevant because the central Government uses it as an instrument to control local fiscal policies: A city council is not allowed to subscribe to new debts unless this index lies below a given threshold established by the Government.
- 6. Provision of Services (PS): Per-capita expenditure for the provision of community services not directly supplied by the city council, e.g. waste management and public transports, and for professional services, such as legal or other technical works, purchased by the city council.
- 7. Purchase of Real Estate (PRE): Expenditure for the acquisition of terrains or other already existing estates (e.g. buildings), booked to the accounts of the year.
- 8. Capital Expenditure (CE): Expenditure for the acquisition of capital goods, booked to the accounts of the year. This is a heading of the balance sheet of a local authority named "Titolo Secondo: Spese in Conto Capitale" composed of ten items that record different types of capital expenses, including the above mentioned 'purchase of real estate'. This heading records the various types of expenses due to the realisation of public works.
- 9. Off Budget Debts (OBD): Debts accrued in the year and not foreseen in the budget. The presence of large and persistent amounts of off-budget debts is a sign of bad management.
- 10. Rate of Dependence on Government Transfers (RDGT): Current Government Transfers/Current Revenues. This ratio measures the share of funding coming from the Public Administration.

The observed values of these variables are taken from the yearly official budgets of the municipalities that compose the above-described sample, taken from two different datasets. The first is "AIDA Public Administration", a database produced by Bureau Van Dijk that contains financial and budget data of local Italian public bodies. The second source that we use is a government database named "Certificati Consuntivi degli Enti Locali" (Balance-sheets of Local Authorities), held by the Ministry of the Interior. It contains the most important financial parameters, indicators and financial ratios that Italian local authorities must communicate to the central government on a yearly base. The data collected about each municipality in the "corrupt" sample cover the three years preceding the year of dismissal of the

city council.¹⁹ To match the time profile of the data of the two groups, we coupled each municipality in the "corrupt" sample with one or two in the "healthy" sample, choosing the ones with the most similar population size and collecting data about the latter over the same years of the former.²⁰

It is worth remarking that none of the above balance-sheet ratios and variables is directly related to the administrative irregularities that may lead to the investigation and subsequent dismissal of a municipality. The administrative irregularities that attract the attention of investigators are unlawful or illicit procedures in public spending such as auction disturbances, illegitimate administrative acts in the procurement of public works and services, over-invoicing, evidence of favouritism in the selection procedures of employees and suppliers, etc. While such anomalies in the management of a City Council can lead to high levels of spending in public works and services, large debt indexes or result in large off-budget debts, the magnitudes of these expenditures and liabilities are not considered signals of mafia infiltration. Indeed, none of the municipalities in our corrupt sample has been investigated and dismissed based on anomalous values of one or more of the above listed balance-sheet variables. Therefore, we do not risk facing problems of endogeneity in our statistical analysis.

The following tables present the mean and the median values of these variables for the two groups of city councils:

The comparison shows that, on average, the corrupt group performs consistently worse that the healthy group with respect to the arrears of both tax collection (TRAI) and payments (PAI), with the values of TRAI and PAI of the corrupt group being roughly one and half time larger than the corresponding values of the healthy group. Not surprisingly, this problem of accumulation of arrears shows up also in the rate at which the two groups manage to dispose of these arrears, as shown by the values of the variables CTA and PPA of the corrupt group that are markedly smaller than the corresponding ones of the healthy group.

The corrupt group spends less that the healthy group in passive interests. As shown by the variable DI, the share of revenues that, on average, the infiltrated municipalities spend on interests is circa 10% smaller than the corresponding share of the healthy city councils. This implies that the corrupt municipalities are, on average, less indebted than healthy municipalities, which is surprising. Moreover, both the mean and the median values

¹⁹The variables 6,7,8 and 9 have been indexed using the yearly Consumer Price Index provided by the 'Istituto Nazionale di Statistica', taking the CPI of year 2010 equal to 100

²⁰This method to match the time profile of the two groups in an LDA was applied by Altman (1968).

Group 'Healthy'										
Mean Values	TRAI	PAI	СТА	PPA	DI	P RE	CE	PS	OBD	RDGT
Mean of Years [-1,-2,-3] Mean Values	0.2637	0.2885	0.4403	0.4551	0.0412	947,445.17	1,816,262.16	282.13	118,534.00	0.0678
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Median Values	TRAI	PAI	СТА	PPA	DI	PRE	CE	PS	OBD	RDGT
Median of Years [-1,-2,-3] Mean Values	0.2524	0.2773	0.4580	0.4392	0.0874	449, 107. 30	821,067.25	256.82	832.48	0.0533
Group 'Corrupt'										
Mean Values	TRAI	PAI	СТА	PPA	DI	P RE	CE	PS	OBD	RDGT
Mean of Years [-1,-2,-3] Mean Values	0.3975	0.4398	0.1960	0.2429	0.0398	144,026.45	266, 759. 79	158.16	223,681.63	0.2141
Median Values	TRAI	PAI	CTA	PPA	DI	PRE	CE	P5	OBD	RDGT
Medlan of Years [-1,-2,-3] Mean Values	0.4073	0.4567	0.1599	0.2135	0.0365	70,374.14	84,402.33	143.01	33,063.35	0.2100
Difference in Means (t-test)	<0.001	<0.001	<0.001	< 0.001	0.735	<0.001	<0.001	<0.001	0.1303	<0.001

of DI in both groups are well below the threshold value that would prevent a city council from increasing its funding through debts.²¹

Interestingly, also the capital expenditures mark a sharp difference between the two groups. The values of both the CE and the PRE variables consistently display a noticeable gap between the healthy and the corrupt groups, with the former spending amounts much larger than the latter. This datum is surprising in as much as the procurement for public works, captured by CE, and the purchase of estates are known to be a fertile ground for frauds, bribery and other illegal rent-seeking behaviours. The expenses for the provision of services also show a significant difference between the two groups, with the healthy city council spending more than the infiltrated ones. Finally, the off-budget debts (OBD) and the financial dependence on Government funding (RDGT) also show a remarkable difference between the two groups, with the infiltrated city councils performing markedly worse than the other group.

 $^{^{21}}$ This threshold, set by the Government as a fiscal policy measure, ranged between 0.08 and 0.12 in the last decade.

4 The statistical analysis

Our statistical analysis is divided into two parts. In the first part we derive a discriminant function through a multivariate Linear Discriminant Analysis,²² where the training set is the above described two-classes sample of city councils and the discriminant function is estimated using the ten balance-sheet variables described in the previous section. We obtain a simple classifier that we named 'Mafia Infiltration Warning Indicator' - a linear combination of the values of the above ten variables – that discriminates between municipalities infiltrated by a mafia and municipalities that do not face this problem. In the second part, we use the above variables to run logistic regressions that deliver estimates of the parameters of a binary logistic model in which the dichotomous dependent variable is the state of a city council: infiltrated or not infiltrated by a mafia. The model provides a measure of the probability that a given city council is affected by a mafia infiltration, a linear combination of budget variables that we call the 'Mafia Infiltration Probability' indicator. In both these applications, we take the average of the above variables computed over the three years preceding the dismissal year.

4.1 Linear Discriminant Analysis

The LDA delivers the following classifier:

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MIWI = -0.3415 \cdot TRAI + 0.3492 \cdot PAI + 0.0594 \cdot CTA + 0.3788 \cdot PPA + 0.2345 \cdot DI + 0.0801 \cdot PRE + 0.2148 \cdot CE + 0.1639 \cdot PS - 0.2447 \cdot OBD - 0.7863 \cdot RDGT.
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The following standard diagnostics for LDA's measure the reliability and the accuracy of the above classifier, that appears reliable and accurate.

To validate the above LDA we run the 'leave-one-out' cross-validation test and a K-Fold cross-validation test, the latter with a 70%-30% random partition of the training set. The former correctly classifies 48 out of 57 infiltrated municipalities and 93 out of 100 non-infiltrated municipalities, delivering a 0.898 level of accuracy. The K-Fold test trains the LDA on 106 municipalities (70% of 157) and tests its results on the remaining 51 municipalities, obtaining an accuracy equal to 0.915.

²²Multivariate linear discriminant analysis became popular in economics and finance thanks to the seminal work by Edward Altman (1968), who applied it to obtain a classifier of the financial status of a company, known as Altman's 'z- score'. See also Altman (2000, 2013) for updates of the original work.

Predicted Class

Actual CLass

	corrupt	healthy
corrupt	49 True Positive	8 False Negative
healthy	6 False Positive	94 True Negative

ACCURACY	0,910	143 out of 157 city councils are correctly classified
PRECISION	0,890	49 out of 55 city councils classified as 'corrupt' are correctly classified
Probability of false alarm [FP/(TP+FP)]	0,109	Probability of classifying a healthy city council as corrupt
RECALL (SENSITIVITY)	0,860	49 out of 57 corrupt city councils are correctly classified
sреанату	0,921	94 out of 102 healthy city councils are correctly classified
Probability of missed alarm [FN/(TN+FN)]	0,078	Probability of classifying a corrupt city council as healthy

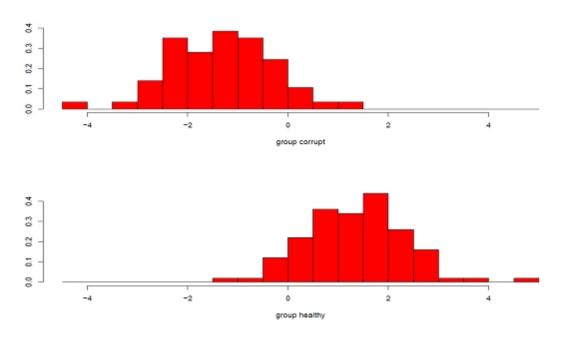


Figure 1: Distribution of the MIWI

It is worth noting that four out six 'healthy' municipalities classified as infiltrated, the 'false positives', are located in southern regions—namely Altomonte and Canna in Calabria, Nicosia in Sicily and Acquara in Campania—in which the mafias have a diffused control over the territories. Moreover, the other two 'false positives', Pomezia and Riese Pio X, are respectively located in Lazio and Veneto, two regions also affected by mafia-related activities. In the light of this prior, these may well be cases of mafia-infiltrated city councils that have not (yet) been discovered and dismissed.

Using stepwise backward elimination procedures – based on the Wald F, Likelihood ratio and chi-square tests – we selected the ten logistic regressions presented in the following table. The dependent variable of these logistic regressions is the logarithm of the ratio between the probabilities of the two states: infiltrated or not infiltrated.²³

The ten alternative configurations of the logit model stem from the fact that three pairs of independent variables display high levels of correlation. The Pearson correlation coefficient between the indexes of tax collection arrears (TRAI) and of payment arrears (PAI) is 0.797, between the rate of

 $^{^{23}}$ As customary, the logistic regression are run merging the 'corrupt' and the 'healthy' samples.

Signif. codes:	Chi-Square Gn? Test (p-vaive)	Accuracy	C statistic (AUC)	WaldTest (Pr(>F))	LogLik	AIC	Pseudo R² (McFadden)		RDTF	OBSD	757.6	DCDC	£	2	PRE	!	9		DDA	CTA	2	PAI	IRAI		intercept	40100000	Independent Variables
	>0.98	0.94	0.99	0.0008222***	-21.7	57.3	0.789	[3,799]	2,4408***	1.2909*** [2.578]					-7.2783*** [-3.519]	[-2.831]	-1.6788***	[-3.065]	-2.2820***		[2.604]	1.935***			[-3.887]	-3 6211***	Model 1
.***, 0.01 ,**, 0.02 ,*, 0.1	>0.98	0.92	0.97	0.0000205***	-34.3	80.6	0.667	[4,135]	2,3023***				[-3.002]	-3.2483***		[-2.251]	-0.8222**	[-3.042]	-1.5919***				[2.101]	0.9537**	[-3,757]	-1.9906***	Model 2
'*' 0.1	>0.98	0.92	0.97	0.0000243***	-33.2	78.3	0.678	[4.077]	2.1712***				[-3.387]	-3.4469***		[-2.512]	-1.0631**			-1.2009** [2.566]	[3.010]	1.5736***			[-4,023]	-1.9157***	Model 3
Z values within brackets	>0.98	0.91	0.96	0.0000026***	-39.0	89.9	0.621	[3,903]	1.6587***		[-2.215]	-1.3606**				[-2.452]	-0.8684**	[-3.174]	-1,44635***				[2.753]	1.1014***	[-3,805]	-1.4317***	Model 4
n brackets	>0.98	0.90	0.93	0.0000001***	-47.0	102.0	0.543								-4.0988*** [-3.523]			[-3.936]	-1.4415***		[3.236]	1.2093***			[-3.940]	-1.9161***	Model 5
	≫.98	0.87	0.92	0.0000000***	-55.7	119.5	0.458				[-3618]	-1.7787***						[-3.716]	-1.1996***				[3.105]	0.9489***	[-4,225]	-1.1979***	Model 6
	>0.98	0.87	0.92	0.000001***	-53.1	114.1	0.484						[-3.278]	-3.3586***				[-3.170]	-1.0862***				[2.975]	1.0043***	[-3,809]	-1 786***	Model 7
	×0.98	0.90	0.94	0.0000011***	-46.1	102.2	0.552			1.1310*** [2.958]			[-3.977]	-6.7348***				[-1.951]	-0.7946*	-1.1210*** [-2.684]					[-4,450]	-3 2142***	Model 8
	>0.98	0.90	0.93	0.0000002***	-48.7	107.5	0.526			16	[-2.242]	-1.2273**	[-3.154]	-3.0422***				[-1.836]	-0.7257*	-1.1321*** [-2.666]					[-4.491]	-2.0552***	Model 9
	>0.98	0.89	0.96	0.0000010***	-39.3	86.7	0.617	[4.215]	2.0381***				[-3.372]	-3.5685***				[-4,696]	-1.9505***						[4.156]	-2.0575***	Model 10

disposal of tax arrears (CTA) and of payment arrears (PPA) is 0.755 and is equal to 0.786 between the purchase of real estates (PRE) and the capital expenditure (CE). The consequent multicollinearity that emerges when these pairs are in the same regression strongly affects the levels of significance of the estimated coefficients as well as other diagnostics.

All models deliver good diagnostics, high classification accuracy and highly significant coefficients, all with the right sign.²⁴ Model 1 performs slightly better than the others in terms of goodness-of-fit (higher pseudo-R²) and also in comparison to the other models, as shown by the 'Akaike Information Criterion' and the log-likelihood ratio test. The goodness of fit of all models is confirmed by the high values of the 'Pearson chi-square goodness-of-fit' test and the AUC (area under curve) of the ROC curves.²⁵ The results of the Wald tests, all smaller than 0.05, show that all models have a high joint significance of the estimated coefficients and good explanatory power. On the whole, we observe a discrete uniformity of the magnitude of the estimated coefficients²⁶ and of their significance levels across the models, apart from the relatively large values that model 1 assigns to the coefficient of PRE and that model 8 assigns to the coefficient of CE. We notice the good performance of models 8-9, with four independent variables, and of models 5-6-7-10 that use just three independent variables. Overall, these results show the significance of the observed regularities in the balance-sheet data of the 'corrupt' sample. To wit, they capture the administrative profile of the municipalities infiltrated by a mafia. This profile is characterised by i) bad performance in the formation and disposal of revenues and payments arrears; ii) low levels of capital expenditures, of expenditures for the acquisition of real estates and, to a lesser extent, for the provision of services; iii) low levels of indebtedness and high dependence on the flows of Government funding; and iv) large values of off-budget debts.

4.2 Testing the results on new dismissal cases

To further test the reliability of our results, we apply the above indicators MIWI and MIP's to the set of city councils dismissed in Italy between September 2016 and November 2017. This set is composed of twenty-four municipalities, fourteen of which are located in Calabria, three in Sicily, five in Campania, one in Apulia (Parabita) and one in Liguria (Lavagna).

²⁴The signs of the coefficients are coherent with the differences in the mean and median values of the variables between the two groups.

²⁵The Hosmer and Lemeshow test of goodness of fit, not reported in the table, yields results aligned to the results of the Pearson chi-square test.

 $^{^{26}}$ As customary, all the variables used in the regressions have been standardised.

	Dismissed city councils	Classified	Prob(infiltr.)
1	BORGETTO	corrupt	0.977
2	BOVA MARINA	corrupt	0.816
3	BRANCALEONE	healthy	0.242
4	CANOLO	corrupt	0.578
5	CASAVATORE	healthy	0.327
6	CASSANO ALL'IONIO	corrupt	0.715
7	CASTELVETRANO	corrupt	0.831
8	CRISPANO	corrupt	0.703
9	CROPANI	healthy	0.404
10	GIOIA TAURO	corrupt	0.931
11	ISOLA DI CAPO RIZZUTO	corrupt	0.969
12	LAMEZIA TERME	corrupt	0.724
13	LAUREANA DI BORRELLO	healthy	0.342
14	LAVAGNA	healthy	0.002
15	MARANO DI NAPOLI	corrupt	0.515
16	MARINA DI GIOIOSA IONICA	corrupt	0.889
17	NICOTERA	corrupt	0.682
18	PALAZZO ADRIANO	corrupt	0.998
19	PARABITA	healthy	0.140
20	PETRONÀ	healthy	0.095
21	RIZZICONI	corrupt	0.593
22	SAN FELICE A CANCELLO	healthy	0.137
23	SCAFATI	corrupt	0.852
24	SORBO SAN BASILE	healthy	0.039

The following table shows the result of the MIWI classifier.

The probability of being infiltrated, fourth column, is computed based on the above MIWI.²⁷ The model fails to classify nine municipalities correctly. The most noticeable error is Lavagna, with an estimated probability of infiltration equal to 0.02. This municipality has an administrative profile

$$P(g = c|X_i) = f_c(X_i)P(g = c)/[(f_c(X_i)P(g = c) + f_h(X_i)P(g = h)]$$

where $P(g = c|X_i)$ is the probability that the City Council *i* belongs to the class 'corrupt', given the data vector X_i , P(g = c) and P(g = h) are the prior probabilities of the two classes - in our case they are equals, because the groups are composed of the same number of elements - $f_c(X_i)$ and $f_h(X_i)$ are, respectively, the probability densities of data X_i if X_i comes from group c and if X_i comes from group h. The LDA package assumes

²⁷These probabilities are computed by the LDA package of the free software environment for statistical computing 'R'. They are calculated using Bayes theorem:

well aligned to the one of the 'healthy' group. This fact is plausibly explained by the fact that the infiltration (by a 'Ndrangheta clan) was short-lived. A judicial investigation led to the arrest of some of Lavagna's administrators in March 2016.²⁸ According to this investigation, the infiltration started with the local elections held in May 2014. The control of 'Ndrangheta over this city council had no sufficient time to affect its policies. The balance sheets of the other municipalities reveal administrative patterns partially different from the one of the 'corrupt' group. The balance-sheet items that do not match the profile of mafia-infiltrated city council are i) the capital expenses (CE and PRE) in municipalities number 5, 14, 20 and 22; ii) the formation and disposal of arrears (TRAI, PAI, CTA and PPA), in municipalities number 9, 13, 19 and 24; iii) the levels of dependence on Government funding (RDGT), in municipalities number 3, 5, 20, 22 and 24; iv) the expenses for the provision of services (PSPC), in municipality number 3.

The administrative profile of these nine municipalities tends to escape the detecting power of our models, as confirmed by the fact that some of our logistic models fail to indicate them as likely cases of infiltration. The table below reports the Mafia Infiltration Probabilities assigned by each logit model to the newly dismissed local authorities:²⁹

4.3 Comments on the results

The results obtained with the LDA and with the logistic regressions show that all the ten balance-sheet variables considered above are useful in discriminating between the two classes and in assessing the probability that a municipality suffers a mafia infiltration. However, some variables appear to be more relevant than others in depicting the phenomenon at hand.

The pairs (TRAI, CTA) and (PAI, PPA) appear (in alternation) in all above regressions with highly significant coefficients. The LDA also assigns to these variables a relevant discriminating role. These variables capture what can be called the 'arrears policy' of infiltrated municipalities. These admin-

that these probabilities are normal and estimates them as follows:

$$f_c(X_i) = \frac{1}{\left[2\pi (detCOV)\right]^{1/2}} e^{-1/2(X_i - \mu_c)^T \left[COV^{-1}(X_i - \mu_c)\right]}$$

where COV is the LDA covariance matrix and μ_c is the vector of group means for data X.

²⁸This investigation, concerning the activities of the 'Ndrangheta clan 'Grande Arcuri' in Liguria, started in 2013 after the discovery of an arsenal.

²⁹The inversion of the dependent variable of the above regressions, $\ln \frac{\Pr(corrupt)}{\Pr(healthy)}$, delivers these probabilities.

DOUGRETTO DOUGRET MODURE		202421	randal o	מובל במי	70141	, A) L	71110	74-1-1	na del q	201210	Madal 10
0.920	BORGETTO	0.915	0.994	0.994	0.970	0.167	0.500	0.360	0.529	0.740	0.994
No.135 No.242 No.146 No.242 No.243 No.146 No.243 No.146 No.244 No.146 No.244 N	BOVA MARINA	0.920	0.877	0.909	0.762	0.882	0.750	0.840	0.779	0.784	0.848
U.0.613 U.9712 U.817 U.829 U.387 U.0004 U.0.543 U.0.548 U.0.508 U.0.6004 U.0.728 U	BRANCALEONE	0./15	0.392	0.676	0.282	6T8'0	0.487	0.714	0.793	0.746	0.291
NIC 0.000	CVNOTO	0.613	0.942	0.81/	0.829	/8T.0	0.7100	0.543	0.639	849.0	688.0
NIC 0.001 0.679 0.799 0.867 0.002 0.352 0.082 0.015 0.170 0.870 0.8870 0.888 0.963 0.745 0.132 0.136 0.126 0.121 0.157 0.262 0.264 0.264 0.264 0.264 0.262 0.264 0.262 0.264 0.264 0.262 0.264 0.262 0.264 0.262 0.262 0.264 0.262 0	CASAVATORE	0.000	0.183	0.193	0.615	0.004	0.728	0./100	0.033	0.2/11	0.0/10
0.870 0.898 0.963 0.745 0.132 0.126 0.121 0.157 0.262 0.264 0.906 0.500 0.934 0.468 0.930 0.913 0.705 0.819 0.677 0.439 0.705 0.298 0.752 0.449 0.566 0.643 0.629 0.946 0.094 0.961 0.838 0.927 0.701 0.745 0.950 0.945 0.024 0.026 0.919 0.583 0.616 0.638 0.419 0.672 0.024 0.174 0.291 0.465 0.138 0.629 0.603 0.002 0.003 0.010 0.046 0.823 0.621 0.638 0.419 0.655 0.011 0.003 0.046 0.394 0.083 0.027 0.026 0.045 0.128 0.001 0.020 0.957 0.774 0.876 0.764 0.712 0.705 0.438 0.001 0.020 0.398 0.999 0.767 0.563 0.911 0.739 0.781 0.001 0.021 0.120 0.128 0.056 0.525 0.001 0.022 0.135 0.148 0.566 0.530 0.781 0.001 0.027 0.037 0.145 0.048 0.249 0.247 0.072 0.000 0.002 0.037 0.415 0.885 0.525 0.000 0.004 0.872 0.008 0.525 0.149 0.000 0.004 0.872 0.008 0.525 0.149 0.000 0.004 0.821 0.885 0.525 0.140 0.035 0.000 0.004 0.821 0.885 0.525 0.000 0.004 0.821 0.885 0.525 0.000 0.004 0.821 0.885 0.525 0.000 0.004 0.821 0.885 0.525 0.000 0.004 0.821 0.885 0.525 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.525 0.140 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.008 0.000 0.004 0.004 0.004 0.000 0.004 0.004 0.004 0.000 0.004 0.004 0.004 0.000 0.004 0.004 0.004 0.000	CASSANO ALL'IONIO	0.001	0.679	0.799	0.867	0.002	0.352	0.082	0.015	0.170	0.268
D.254 D.906 D.500 D.934 D.463 D.530 D.913 D.705 D.819	CASTELVETRANO	0.870	0.898	0.963	0.745	0.132	0.126	0.121	0.157	0.262	0.807
D.677 D.439 D.705 D.298 D.752 D.449 D.566 D.643 D.629	CRISPANO	0.264	0.906	0.500	0.934	0.463	0.530	0.913	0.705	0.819	0.696
D.946 D.954 D.950 D.961 D.836 D.937 D.701 D.745 D.950 D.859 D.859 D.855 D.986 D.919 D.583 D.816 D.937 D.701 D.745 D.950 D.859 D.859 D.859 D.859 D.859 D.986 D.919 D.583 D.816 D.638 D.419 D.672 D.942 D.942 D.946 D.948 D.946 D.946 D.946 D.948 D.946 D.946 D.946 D.948 D.946 D.946 D.946 D.948 D.946 D.94	CROPANI	0.677	0.435	0.705	0.298	0.752	0.449	0.566	0.643	0.629	0.503
ZZUITC 0.859 0.875 0.986 0.919 0.583 0.816 0.638 0.419 0.672 FRELLO 0.141 0.466 0.391 0.465 0.138 0.618 0.157 0.650 0.555 OIII 0.002 0.003 0.010 0.004 0.083 0.027 0.026 0.045 0.128 OIII 0.003 0.010 0.046 0.083 0.027 0.026 0.045 0.128 OIII 0.003 0.040 0.390 0.007 0.563 0.094 0.659 0.433 0.834 IONICA 0.926 0.044 0.093 0.007 0.563 0.094 0.659 0.433 0.854 IONICA 0.936 0.977 0.775 0.774 0.803 0.704 0.712 0.705 0.433 0.001 0.0220 0.1785 0.993 0.767 0.862 0.911 0.789 0.781 0.041 0.0219 0.185 0.048 0.0249	GIOIA TAURO	0.946	0.934	0.960	0.961	958.0	0.937	0.701	0.745	0.950	0.957
CA242 CA.174 CA.291 CA.465 CA.138 CA.138 CA.184 CA.555 CA.565 CA.555 CA.565 CA.555 CA.565 CA.565 CA.565 CA.565 CA.565 CA.565 CA.889 COLI CA.002 CA.003 CA.010 CA.004 CA.822 CA.144 CA.813 CA.555 CA.889 COLI CA.003 CA.003 CA.010 CA.004 CA.083 CA.277 CA.265 CA.284 CA.128 COLI CA.003 CA.010 CA.003 CA.010 CA.004 CA.0083 CA.704 CA.704 CA.704 CA.704 CA.704 CA.704 CA.705 CA.743 CA.744 CA.704 CA.712 CA.705 CA.743 CA.744 CA.704 CA.712 CA.743 CA.749 CA.743 CA.749 CA.744 CA.744 CA.744 CA.744 CA.744 CA.744 CA.744 CA.745 CA.745 CA.745 CA.745 CA.745 CA.745 CA.745 CA.745 CA.745 CA.7	ISOLA DI CAPO RIZZUTO	0.859	0.875	0.986	0.919	0.583	0.816	0.638	0.419	0.672	0.618
FREILO 0.141 0.4GG 0.304 0.34G 0.822 0.814 0.813 0.855 0.889 OII 0.002 0.003 0.010 0.004 0.083 0.027 0.026 0.045 0.128 OII 0.003 0.096 0.046 0.390 0.007 0.563 0.094 0.659 0.433 IO 1.000 0.940 0.957 0.774 0.863 0.763 0.794 0.735 0.749 IO 1.000 1.000 0.998 0.999 0.767 0.862 0.911 0.783 0.781 IO 0.051 0.219 0.185 0.198 0.999 0.767 0.862 0.911 0.783 0.781 ICELLO 0.091 0.729 0.185 0.158 0.566 0.530 0.792 0.863 IE 0.186 0.027 0.037 0.415 0.088 0.426 0.01 0.025 0.436 IE 0.186 0.0	LAMEZIA TERME	0.242	0.174	0.291	0.465	0.138	0.618	0.157	0.650	0.555	0.341
OII 0.002 0.003 0.010 0.004 0.083 0.027 0.026 0.045 0.128 OIII 0.003 0.096 0.046 0.390 0.007 0.563 0.094 0.659 0.438 SSA IONICA 0.926 0.840 0.957 0.774 0.878 0.774 0.878 0.774 0.878 O.001 1.000 0.938 0.999 0.767 0.862 0.911 0.783 0.781 O.001 0.220 0.120 0.122 0.008 0.249 0.247 0.072 0.783 O.911 0.755 0.879 0.691 0.885 0.590 0.581 0.745 0.783 O.911 0.755 0.879 0.691 0.885 0.590 0.581 0.792 0.863 O.900 0.027 0.037 0.715 0.008 0.822 0.136 0.025 0.895 O.186 0.096 0.281 0.038 0.555 0.410 0.326 0.515 0.384 O.500 0.500 0.583 0.583 0.500 0.625 0.542 0.657 0.625	LAUREANA DI BORRELLO	0.141	0.466	0.304	0.346	0.822	0.814	0.813	0.855	0.889	⊕ 839
OIII 0.003 0.096 0.046 0.890 0.007 0.563 0.094 0.659 0.433 SSA IONICA 0.926 0.840 0.957 0.774 0.808 0.704 0.712 0.705 0.749 IO 1.000 1.000 0.998 0.999 0.767 0.862 0.911 0.738 0.781 0.001 0.220 0.120 0.292 0.008 0.249 0.247 0.072 0.781 0.911 0.755 0.849 0.566 0.540 0.581 0.783 0.781 0.941 0.755 0.849 0.691 0.885 0.792 0.853 0.792 0.853 0.940 0.027 0.037 0.715 0.008 0.822 0.136 0.025 0.863 0.000 0.404 0.824 0.872 0.008 0.822 0.136 0.025 0.436 0.500 0.583 0.583 0.555 0.110 0.326 0.515 0.384 </td <td>LAVAGNA</td> <td>0.002</td> <td>0.003</td> <td>0.010</td> <td>0.004</td> <td>0.083</td> <td>0.027</td> <td>0.026</td> <td>0.045</td> <td>0.128</td> <td>02011</td>	LAVAGNA	0.002	0.003	0.010	0.004	0.083	0.027	0.026	0.045	0.128	02011
SSA IONICA 0.976 0.840 0.957 0.774 0.808 0.704 0.712 0.705 0.749 IO 1.000 1.000 0.998 0.999 0.767 0.862 0.911 0.785 0.781 IO 1.0001 0.220 0.120 0.299 0.767 0.862 0.911 0.789 0.781 IO 0.001 0.220 0.120 0.292 0.008 0.249 0.247 0.072 0.781 IO 0.091 0.220 0.185 0.158 0.566 0.530 0.581 0.735 0.781 IO 0.091 0.221 0.185 0.158 0.566 0.530 0.581 0.735 0.781 IO 0.000 0.027 0.037 0.415 0.085 0.822 0.136 0.025 0.436 IE 0.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 IE 0.500 0.5	MARANO DI NAPOLI	0.003	0.096	0.046	0.390	0.007	0.563	0.094	0.659	0.433	0.259
O. 833 O. 797 O. 785 O. 903 O. 795 O. 913 O. 785 O. 908 IO 1.000 1.000 O. 998 O. 999 O. 767 O. 862 O. 911 O. 783 O. 781 0.001 0.220 0.120 0.292 0.008 0.249 0.247 0.072 0.124 0.091 0.051 0.129 0.186 0.566 0.530 0.581 0.783 0.783 0.911 0.055 0.849 0.056 0.530 0.581 0.735 0.783 0.000 0.002 0.037 0.715 0.008 0.822 0.136 0.025 0.436 0.186 0.096 0.281 0.872 0.000 0.476 0.026 0.001 0.089 12 12 10 10 12 9 11 3 9 0.500 0.500 0.503 0.503 0.503 0.500 0.625 0.542 0.542 0.625	MARINA DI GIOIOSA IONICA	0.926	0.840	0.957	0.774	808.0	0.704	0.712	0.705	0.749	0.768
100	NICOTERA	0.833	0.797	0.785	0.903	0.799	0.913	0.785	0.728	0.908	0.701
0.001 0.220 0.120 0.292 0.008 0.249 0.247 0.072 0.124 0.051 0.219 0.185 0.158 0.566 0.530 0.581 0.735 0.783 0.941 0.755 0.849 0.691 0.885 0.735 0.792 0.853 0.863 0.000 0.0027 0.037 0.415 0.008 0.822 0.136 0.025 0.436 0.000 0.404 0.824 0.872 0.000 0.476 0.026 0.001 0.089 E 0.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.560 0.625 0.542 0.657 0.625	PALAZZO ADRIANO	T.000	1.000	0.998	0.999	0.767	0.862	0.911	0.789	0.781	0.999
0.051 0.219 0.185 0.158 0.566 0.530 0.581 0.735 0.783 0.941 0.755 0.849 0.691 0.885 0.735 0.792 0.863 0.863 0.000 0.0027 0.037 0.715 0.008 0.822 0.136 0.025 0.736 0.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 12 12 10 10 12 9 11 8 9 0.500 0.500 0.583 0.583 0.500 0.625 0.542 0.657 0.625	PARABITA	0.001	0.220	0.120	0.292	800.0	0.249	0.247	0.072	0.124	0.073
0.941 0.755 0.849 0.691 0.885 0.735 0.792 0.853 0.863 OCELLO 0.000 0.027 0.037 0.415 0.008 0.822 0.136 0.025 0.436 D.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.583 0.500 0.625 0.542 0.542 0.657 0.625	PEIRONÀ	0.051	0.219	0.185	0.158	0.566	0.530	0.581	0.735	0.783	0.545
ICELLO 0.000 0.027 0.037 0.415 0.008 0.822 0.136 0.025 0.436 0.000 0.404 0.824 0.872 0.000 0.476 0.026 0.001 0.089 E 0.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.583 0.500 0.625 0.542 0.657 0.625	HIZZICONI	0.941	0.755	0.849	0.691	0.885	0./35	0.792	0.855	0.863	0.696
0.000 0.404 0.824 0.872 0.000 0.476 0.026 0.001 0.089 0.186 0.096 0.281 0.038 0.555 0.110 0.326 0.515 0.384 12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.583 0.500 0.625 0.542 0.657 0.625	SAN FELICE A CANCELLO	0.000	0.027	0.037	0./115	800.0	0.822	0.136	0.025	0./136	0.048
12 12 12 10 0.583 0.583 0.550 0.110 0.326 0.515 0.384 0.500 0.500 0.583 0.583 0.500 0.625 0.542 0.657 0.625	SCAFATI	0.000	0.404	0.824	0.872	0.000	0.476	0.026	0.001	0.089	0.201
12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.500 0.625 0.542 0.657 0.625	SORBO SAN BASILE	0.186	0.096	0.281	0.038	0.555	0.110	0.326	0.516	0.384	0.154
12 12 10 10 12 9 11 3 9 0.500 0.500 0.583 0.500 0.625 0.542 0.657 0.625											
0.500 0.500 0.503 0.503 0.500 0.625 0.542 0.657 0.625	Prediction errors	12	12	10	10	12	9	11	8	o	10
	Accuracy	0.500	0.500	0.583	0.583	0.500	0.625	0.542	0.657	0.625	0.583

istrations delay both tax collection and payments and, not surprisingly, they selectively do this. They delay or forego collecting taxes from their 'friends' while delaying payments to individuals and firms who do not have the 'privilege' of having their credits honoured in a timely fashion and, consequently, become game for extortions. Moreover, low levels of tax collection are also useful to acquire and keep the support of electors, reducing the risk of losing control of the local authority and of the consequent benefits.³⁰

The above results show that the low level of indebtedness of corrupt municipalities contributes to the correct classification of the latter. As mentioned above, this behaviour is surprising. Both common sense and empirical evidence suggest that rent-seeking practices in public authorities are often associated with a large resort to debt. Conversely, it is not surprising that infiltrated municipalities have large values of off-budget debts (ODBD) and are more dependent on Government funding (RDGT), both signs of poor administration. We also find that low levels of the per-capita provision of services (PSPC) characterise the profile of infiltrated municipalities. This finding is a further signal of low-quality administration, in as much as these expenses include funding for primary and secondary schools, local transports, waste management, etc.

The most unexpected of our findings is the effect of capital expenditures (CE), that is the expenses for public works, and of the purchase of estates (PRE) on our infiltration indicators. The estimated LDA assigns to both these variables a positive coefficient: the larger these expenses, the less likely the mafia infiltration. This result is even more evident in the logistic regression. Like the pairs (TRAI, CTA) and (PAI, PPA), and for the same reason, the variables CE and PRE appear in alternation in the above logit models and with highly significant coefficients. The magnitudes of their coefficients show that these variables have a substantial impact on our indicators. Like for the LDA, the surprise is in the signs of the coefficients of CE and PRE: the larger these expenses, the smaller the estimated probability of mafia infiltration. As is known, the procurement of public works and the purchase of real estates are often an occasion for rent-seeking and fraudulent behaviours on the part of corrupt politicians. This should apply, a fortiori, to cases of mafia infiltrations. Indeed, the hands of the Italian mafias on the capital expenditures of municipalities became evident in the '90s. As Acconcia et al. (2014) report, "During our sample years [i.e., 1990-1999], indeed, public works managed by local administrations in Italy became one of the most

³⁰An essential part of these illicit benefits comes from activities that do not require funding, such as commercial licencing, urban zoning and building licences, selection of employees and suppliers, etc.

lucrative sources of business for the mafias", [Acconcia et al. (2014), page 2191]. These authors also mention that, according to the Ministero degli Interni (Home Affairs Ministry), over the same period the amount of earnings made by the Italian mafias from the control of the procurement of public works is comparable with the amount they earned through extortion and drug dealing.

We cannot ascribe this behaviour simply to a lack of funding. The infiltrated municipalities in our sample can increase their resources by reducing the arrears of tax collection or even increasing their debts.³¹ We believe that this behaviour is induced by the strengthening of the anti-mafia and anti-corruption policies of the Italian authorities. In 2009 the Italian legislator created the 'Commissione Indipendente di Valutazione Trasparenza ed Integrità³² (i.e. independent commission of evaluation of transparency and integrity), renamed as 'Agenzia Nazionale Anti Corruzione' in 2014. In 2012 the Italian Parliament took a second step in the reinforcement of anti-corruption policies, issuing a law that introduced the 'Piano Nazionale Anticorruzione', implemented at a national, regional and local level.³³ These anti-corruption policies yielded strict monitoring of the procedures of public procurement contracts, increasing the number of investigations and trials concerning these contracts. We think that, as a consequence, rent-seeking administrators have adjusted their behaviour. Facing a higher risk of being detected, the municipalities controlled or influenced by mafia have markedly reduced investments in public works. The tighter controls raised the probability of being caught and, consequently, diminished the expected unlawful returns from capital expenditures. This means that the opportunity cost, in terms of illegal earnings, of a euro of revenues (collected taxes) invested in public works diminished for the same rationale. Thus, the increased monitoring effort of the authorities contributes to explain also the substantial accumulation of tax arrears undertaken by infiltrated municipalities.

5 Conclusions

We study the administrative behaviour of a set of Italian municipalities that have been dismissed by the Government because of mafia infiltrations between 2010 and 2016. We look at their balance-sheet data searching for

³¹Recall that, as shown above, the corrupt group, on average, is characterised by low levels of debt, lower than the healthy group.

 $^{^{32}}$ Decreto Legge n. 150/09.

 $^{^{33}}$ Law n. 190/2012, 'Disposizioni per la prevenzione e la repressione della corruzione e dell'illegalità nella pubblica amministrazione'.

administrative patterns capable of rendering such infiltrations detectable. Indeed, we find a set of observable and significant regularities in their behaviour. The LDA and the logistic regressions presented above depict, in a neat fashion, a specific administrative profile of these city councils. The above results show that these municipalities are characterised by i) the accumulation of large amounts of arrears, both in the tax collection and in the payments, along with low rates of disposal of such arrears; ii) moderate levels of indebteness; iii) large values of off-budget debts, high dependence on Government funding and relatively small expenditures in the provision of services, all signs of poor administration.

Moreover, low levels of capital expenditure, i.e. expenses for public works, appear highly significant in distinguishing between infiltrated and not infiltrated city councils. This is quite surprising in the light of the well-established evidence that indicates the procurement of public works as a major source of earning for mafia organisations, at least up to the beginning of this century. The most plausible explanation of this finding is the fact that the Italian authorities, in the last decade, have intensified their anti-corruption policies and focused part of their efforts on the monitoring of the procurement of public works.

There is a broad consensus about the importance of the judicial systems and of the mechanisms of law enforcement, at a national and regional level, in shaping the rent-seeking strategies of corrupt public administrators as well as the strategies undertaken by mafia organisations. Our results confirm this opinion and show that the administrative practices of mafia-infiltrated city councils in Italy can sharply change, even in a relatively brief lapse of time, in response to changes in anti-corruption and anti-mafia policies.

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N.	City Council	Province	Region	Date of Dismissal
1	Borgia	Catanzaro	Calabria	02/07/2010
2	Gricignano di Aversa	Caserta	Campania	02/08/2010
3	Nicotera	Vibo Valentia	Calabria	13/08/2010
4	Condofuri	Reggio Calabria	Calabria	12/10/2010
5	San Procopio	Reggio Calabria	Calabria	23/12/2010
6	Roccaforte del Greco	Reggio Calabria	Calabria	28/02/2011
7	Castrofilippo	Agrigento	Sicilia	18/04/2011
8	Corigliano Calabro	Cosenza	Calabria	09/06/2011
9	Marina di Gioiosa Ionica	Reggio Calabria	Calabria	07/07/2011
10	Briatico	Vibo Valentia	Calabria	24/01/2012
11	Samo	Reggio Calabria	Calabria	24/01/2012
12	Careri	Reggio Calabria	Calabria	15/02/2012
13	Sant'llario dello Ionio	Reggio Calabria	Calabria	15/02/2012
14	Bova Marina	Reggio Calabria	Calabria	30/03/2012
15	Gragnano	Salerno	Campania	30/03/2012
16	Leinì	Torino	Piemonte	30/03/2012
17	Pagani	Salerno	Campania	30/03/2012
18	Platì	Reggio Calabria	Calabria	30/03/2012
19	Racalmuto	Agrigento	Sicilia	30/03/2012
20	Salemi	Trapani	Sicilia	30/03/2012
21	Mileto	Vibo Valentia	Calabria	10/04/2012
22	Casal di Principe	Caserta	Campania	17/04/2012
23	Casapesenna	Caserta	Campania	17/04/2012
24	Castel Volturno	Caserta	Campania	17/04/2012
25	Rivarolo Canavese	Torino	Piemonte	22/05/2012
26	Mongiana	Vibo Valentia	Calabria	12/07/2012
27	San Cipriano d'Aversa	Caserta	Campania	14/08/2012
28	Reggio Calabria	Reggio Calabria	Calabria	10/10/2012
29	Isola delle Femmine	Palermo	Sicilia	12/11/2012
30	Augusta	Siracusa	Sicilia	07/03/2013

Figure 2: Sa27ple 'corrupt'

N.	City Council	Province	Region	Date of Dismissal
31	Mascali	Catania	Sicilia	09/04/2013
32	Melito di Porto	Reggio	Calabria	09/04/2013
	Salvo	Calabria		00/04/0040
33	Polizzi Generosa	Palermo	Sicilia	09/04/2013
34	Quarto	Napoli	Campania	09/04/2013
35	San Calogero	Vibo Valentia	Calabria	09/04/2013
36	Siderno	Reggio Calabria	Calabria	09/04/2013
37	Casignana	Reggio Calabria	Calabria	19/04/2013
38	Giugliano	Napoli	Campania	24/04/2013
39	San Luca	Reggio Calabria	Calabria	17/05/2013
40	Ardore	Reggio Calabria	Calabria	27/06/2013
41	Taurianova	Reggio Calabria	Calabria	09/07/2013
42	Sedriano	Milano	Lombardia	21/10/2013
43	Scalea	Cosenza	Calabria	25/02/2014
44	Montelepre	Palermo	Sicilia	13/03/2014
45	Battipaglia	Salerno	Campania	07/04/2014
46	Cellino San Marco	Brindisi	Puglia	19/04/2014
47	Badolato	Catanzaro	Calabria	23/05/2014
48	Africo	Reggio Calabria	Calabria	01/08/2014
49	San Ferdinando	Reggio Calabria	Calabria	31/10/2014
50	Bovalino	Reggio Calabria	Calabria	02/04/2015
51	Bagnara Calabra	Reggio Calabria	Calabria	14/04/2015
52	Arzano	Napoli	Campania	29/04/2015
53	Scicli	Ragusa	Sicilia	29/04/2015
54	Monte Sant'Angelo	Foggia	Puglia	20/07/2015
55	Brescello	Reggio Emilia	Emilia- Romagna	20/04/2016
56	Corleone	Palermo	Sicilia	10/08/2016
57	Tropea	Vibo Valentia	Calabria	10/08/2016

Figure 3: Sample 'corrupt'

N.	City Council	Province	Region
1	ABBADIA SAN SALVATORE	SIENA	TOSCANA
2	ALBA	CUNEO	PIEMONTE
3	ALBANO LAZIALE	ROMA	LAZIO
4	ALTOMONTE	COSENZA	CALABRIA
5	ANDORA	SAVONA	LIGURIA
_	APPIANO SULLA STRADA DEL VINO - EPPAN AN	BOLZANIO	TRENTINO ALTO
6	DER WEINSTRAßE	BOLZANO	ADIGE
7	AQUARA	SALERNO	CAMPANIA
8	BADIA - ARTFI	ROI7ANO	TRENTINO ALTO ADIGE
9	BARONISSI	SALERNO	CAMPANIA
10	BASTIA UMBRA	PERUGIA	UMBRIA
11	BERNALDA	MATERA	BASILICATA
12	BIBBIENA	AREZZO	TOSCANA
13	BONIFATI	COSENZA	CALABRIA
14	BRESSANONE	BOLZANO	TRENTINO ALTO ADIGE
15	BUCCINO	SALERNO	CAMPANIA
16	BUSCA	CUNEO	PIEMONTE
17	CALENZANO	FIRENZE	TOSCANA
18	CAMAIORE	LUCCA	TOSCANA
19	CAMPORA	SALERNO	CAMPANIA
20	CANNA	COSENZA	CALABRIA
21	CAPOLIVERI	LIVORNO	TOSCANA
22	CAPRANICA	VITERRO	I A7I∩
23	CARLENTINI	SIRACUSA	SICILIA
24	CASTELNUOVO MAGRA	LA SPEZIA	LIGURIA
25	CASTIGLIONE DELLAGO	PERUGIA	UMBRIA
26	CASTIGLIONE MESSER MARINO	CHIETI	ABRUZZO
27	CHERASCO	CUNEO	PIEMONTE
28	CITTà DI CASTELLO	PERUGIA	UMBRIA
29	CORCIANO	PERUGIA	UMBRIA
30	CORINALDO	ANCONA	MARCHE
31	CURNO	BERGAMO	LOMBARDIA
32	CURON VENOSTA - GRAUN IM VINSCHGAU	BOLZANO	TRENTINO ALTO ADIGE
33	DOMANICO	COSENZA	CALABRIA
34	ENNA	ENNA	SICILIA
35	FAENZA	RAVENNA	EMILIA-ROMAGNA

Figure 4: Sa29ple 'healthy'

N.	City Council	Province	Region
36	FIRMO	COSENZA	CALABRIA
37	FONDI	LATINA	LAZIO
20	FORMA 77A	VERBANC-	DIEMONTE
38	FORMAZZA	CUSIO-OSSOLA	PIEMONTE
39	FORMIGINE	MODENA	EMILIA ROMAGNA
40	FOSSALTO	CAMPOBASSO	MOLISE
41	FUSIGNANO	RAVENNA	EMILIA-ROMAGNA
42	GAGLIANO CASTELFERRATO	ENNA	SICILIA
43	GIAVERA DEL MONTELLO	TREVISO	VENETO
44	GLORENZA - GLURNS	BOLZANO	TRENTINO ALTO ADIGE
45	GUALDO TADINO	PERUGIA	UMBRIA
46	LIMONE PIEMONTE	CUNEO	PIEMONTE
47	LIVORNO	LIVORNO	TOSCANA
48	MAIOLATI SPONTINI	ANCONA	MARCHE
49	MALEGNO	BRESCIA	LOMBARDIA
50	MARINO	ROMA	LAZIO
51	MASSA LOMBARDA	RAVENNA	EMILIA-ROMAGNA
52	MATERA	MATERA	BASILICATA
53	MELENDUGNO	LECCE	PUGLIA
54	MERANO MERAN	BOLZANO	TRENTINO ALTO ADIGE
55	MEZZAGO	MON7A BRIANZA	LOMBARDIA
56	MIGLIANICO	CHIETI	ABRUZZO
57	MONSANO	ANCONA	MARCHE
58	MONTE ARGENTARIO	GROSSETO	TOSCANA
59	MONTE SAN VITO	ΛΝΟΟΝΛ	MARCHE
60	MONTELUPO FIORENTINO	FIRENZE	TOSCANA
61	NERVESA DELLA BATTAGLIA	TREVISO	VENETO
62	NICOSIA	ENNA	SICILIA
63	OSTRA VETERE	ANCONA	MARCHE
64	PERUGIA	PERUGIA	UMBRIA
65	PIETRASANTA	LUCCA	TOSCANA
66	POCAPAGLIA	CUNEO	PIEMONTE
67	POMEZIA	ROMA	LAZIO
68	PORDENONE	PORDENONE	FRIULI VENEZIA GIULIA
69	PREDAZZO	TRENTO	TRENTINO ALTO ADIGE
70	30 RACINES - RATSCHINGS	BOLZANO	TRENTINO ALTO

Figure 5: Sample 'healthy'

N.	Clty Council	Province	Region
71	RIESE PIO X	TREVISO	VENETO
/2	ROVERE O	IRENIO	TRENTINO ALTO
12	ROVERETO	IKENIO	ADIGE
73	SAN FICR	TREVISO	VENETO
/4	SAN GIOVANNI VALDARNO	AREZZO	TOSCANA
75	SAN LEONARDO IN PASSIRIA - ST. LEONHARD IN	BOLZANO	TRENTINO ALTO
	PASSEIER	BOLZANO	ADIGE
76	SAN LORENZO DI SEBATO - ST. LORENZEN	BOLZANO	TRENTINO ALTO
70	SAN LORENZO DI SEBATO - ST. LORENZEN	BOLZANO	ADIGE
77	SAN VITO DI FAGAGNA	UDINE	FRIULI VENEZIA
//	37/10 DI FAGAGIA7	ODINE	GIULIA
78	SAVONA	SAVONA	LIGURIA
79	SCANZOROSCIATE	BERG∧MO	LOMBARDIA
80	SERAVEZZA	LUCCA	TOSCANA
81	SESTO AL REGHENA	PORDENONE	FRIULI VENEZIA
01	SESTO NE RESTIETA	PORDENONE	GIULIA
82	SIUDI	SUD SARDEGNA	SARDEGNA
- 02	31551	SOD SANDEGIVA	SANDEGIVA
83	SIENA	SIENA	TOSCANA
84	SOLZA	BERGAMO	LOMBARDIA
85	STIGLIANO	MATERA	BASILICATA
86	SUBBIANO	AREZZO	TOSCANA
87	SUSEGANA	TREVISO	VENETO
88	TAVARNELLE VAL DI PESA	FIRENZE	TOSCANA
89	IOLLO	CHIETI	ABRUZZO
90	TORRE D'ISOLA	PAVIA	LOMBARDIA
91	IRENTO	IKENIO	TRENTINO ALTO
	THENTO	THEITTO	ΛDIGE
92	TROINA	ENNA	SICILIA
93	UGEN10	LECCE	PUGLIA
94	UMBERTIDE	PERUGIA	UMBRIA
95	VALDOBBIADENE	TREVISO	VENETO
96	VALMONTONE	ROMA	LAZIO
97	VARNA - VAHRN	BOLZANO	TRENTINO ALTO
	VAINA - VARINI	BOLZANO	ADIGE
98	VIETRI DI POTENZA	POTENZA	BASILICATA
99	VOLTERRA	PISA	TOSCANA
100	ZOLLINO	LECCE	PUGLIA

Figure 6: Sample 'healthy'