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Organised crime and educational outcomes in Southern Italy: An empirical investigation

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ABSTRACT

This paper explores the relationship between the presence of organised crime into the local socio-economic fabric and educational outcomes in Southern Italy. For this purpose, we rely on different indices of organized crime, the main of which is the well-established *Mafia* Presence Index (IPM), a composite indicator capturing manifold dimensions (activities, violence, political, and economic infiltration) of the presence of *Mafia*-type organizations on the national soil. These indices proxy the (scale of) negative *Mafia*-type values that permeate a local society and that are likely to hinder educational achievements, distorting the incentives of both the youngsters (and/or their parents) to invest in human capital and the local firms to employ those who decide to make this investment. Furthermore, combining contemporary individual-level educational outcomes with historical data on *Mafia* infiltration, we control for endogeneity concerns through an IV strategy. We provide evidence that the presence of organised crime at local level significantly decreases the scores achieved by primary school students, undertaking the INVALSI test for literacy in Southern Italy. Our results are robust to the use of different measures of organised crime, to the inclusion of different sets of controls, different subsamples and to relaxing the exclusion restriction in the IV strategy.

1. Introduction

The detrimental effects of organised crime on society and its economic system are well-known in the world. In fact, it negatively affects political activity and policy makers [1–3], the economic output [4], growth and investments [5–7]. Among all the socio-economic features influenced by organised crime, education stands out because of its relevant contribution to economic growth in the long term. The first papers investigating the nexus between education and crime have been [8–10], showing the causal link between education and crime in England and Wales. Then, other scholars have focused on this relationship from the opposite direction, showing that crime can negatively affect the level of economic resources available to education [11], the human capital stock [12] and its accumulation over time [13], and the attitude towards cheating of students taking school exit exams [14].

We contribute this stream of literature by exploring the relationship between the presence of organised crime in the local society and the educational outcomes of students undertaking standardised tests (INVALSI) in the second and fifth grades of primary school in Southern Italy. To measure the presence of organised crime at the local level, we employ the well-established composite index of *Mafia* presence (*Indice di Presenza Mafiosa*, IPM), developed by [15]. To check the robustness of our result, we have constructed a second indicator (*Indice di Infiltrazione Mafiosa*, IIM) that looks at the phenomenon of organised crime from a narrower perspective, namely that of its ability to penetrate local public institutions, to influence their quality and decision-making process.

In this paper, the *Mafia* rooting, and its ability to permanently interact with the local community and to establish (crime) networks of relations are supposed to affect education through different transmission mechanisms. *Mafia*-type values are likely to corrupt the fabric of the local society, impairing human capital accumulation and, hence, harming educational achievements. There are two main channels through which this happens, both of which are related to the distortion of the economic incentives of the agents [13]: the youngsters commit less to education and firms demand fewer personnel with high-level education.

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In the case of very young pupils like those in our paper, these transmission mechanisms also operate through the beliefs and decisions of parents, and the values that they convey to their children. These values risk being severely compromised in a local community that largely adheres to the Mafia principles and rules, thus reducing the importance of school investment for the future of young people. Hence, our paper indirectly relates to the stream of literature focusing on cultural transmission from parents to their children [16]. Indeed, cultural traits, such as obedience to parents and teachers, respect for the law, and tolerance for different opinions represent a package of values that parents inherit, update over the years (based on their life experiences and social interactions), and then pass on to their children [17,18].[1]

Finally, the paper is also related to the literature investigating the relationship between education and crime (for a detailed review, see [20], in the light of the feedback loop relationship existing between the two phenomena. Particularly, [21] show that investments in education can curb criminal behaviour, sometimes even more successfully than law enforcement, because they make the choice of crime more costly. However, the main result of [21] may not always be verified if the environment in which agents live is excessively affected by criminal organizations. In fact, [22] shows that investments in education should be complemented with enough public safety to be effective in reducing criminality and violence. On this vein, looking at Colombia, [23] shows that exposing kids to illegal labour market makes them more likely to be criminals as adults. Similarly, [24] reports the effect of drug-related violence in Mexico on academic outcomes. Finally, [25] show the presence of a causality nexus between high school attendance and adolescent crime, which makes a crime reducing effect of education less likely to occur. Moreover, the authors report that the crime increasing effect found in the South of Italy is consistent with a criminal capital accumulation process, operating through social interactions and crime networks.

Our results show that a debauched local environment due to *Mafia* infiltration in the societal fabric (negatively) affects educational outcomes, as measured by the INVALSI test scores on Italian language achieved by primary school students, after applying the correction for score manipulation suggested by [26]. More specifically, we provide robust evidence that the presence of organised crime at local level significantly decreases the scores achieved by primary school students in Southern Italy who take the INVALSI test for literacy. The results are robust to the use of different measures of organised crime, to the inclusion of different sets of controls, different subsamples and to relaxing the exclusion restriction in the instrumental variables (IV) strategy.

To address endogeneity concerns, in our paper, variables measuring organised crime in Southern Italy are instrumented. We are not the first to do this. Among others, [27] use interactions and instruments to capture the impact of public corruption on banking. In line with the main related literature, we employ, as instruments, measures related to the historical diffusion of *Mafia* in Southern Italian regions. Since the pioneering work of [28] on the historical origins of *Mafia*, contemporary measures of organised crime have been instrumented using geographic and historical variables to capture the institutional, socioeconomic and environmental features of the places where organised crime originally emerged (e.g., [2,29–31]. Specifically, our instruments are the spread of mafia organizations [32] and the land productivity [29] at the end of 19th century in the Southern Italian provinces.

Looking at the possible mechanisms behind the impact of organized crime on INVALSI performance, our findings support the hypothesis that poor educational outcomes in the South of Italy are, *ceteris paribus*, the consequence of a lower level of school engagement (in terms of effort, attendance and compliance) by students living in those local communities where organized crime is more deeply rooted and capable of making the schooling option less attractive (in terms of expected economic payoffs) compared to other crime activities (i.e., drug trafficking, extortion, loansharking, illegal gambling, etc.). All this, ultimately, translates into a reduction in the expected return on investment in human capital and, hence, a lower level of investment itself and a worse school performance.

The rest of the paper is organised as follows. In the next Section, we review the literature on the effects and the measurement of organised crime, with a special focus on the crime-education relationship. Section 3 describes the INVALSI evaluation program and highlights the geographical divide in educational outcomes, whereas Section 4 illustrates the data. Sections 5 and 6 present and discuss the empirical strategy and results. Finally, Section 7 offers some concluding remarks.

2. Organised crime: effects and measurement issues

2.1. The crime-education relationship

Organised crime is commonly perceived as negatively affecting economic systems under different dimensions. Above all, high levels of organised crime can create an unfavourable business climate, which works as disincentive for foreign and national investments [5]. Also, the quality and the accountability of the political class can be badly affected by the presence of organised crime (see [3,33,34]). For instance, [4] looks at the relationship between organised crime and measures of economic and political performance, showing that the presence of organised crime is associated with low levels of per capita economic output. [35] show the long-run macroeconomic consequences of criminal activity in Italy. [7] report the negative effect of high levels of organised crime on foreign and national investments in Italy. In addition, [36] shows the existence of spillover effects on the level of public investments directed to municipalities close to those whose city council has been dismissed because of the presence of *Mafia*-connected officials. [6] shows that the presence of organised crime is the most relevant socio-economic variable negatively correlated to economic development in Italy.

Considering all the possible aspects of a society that can be affected by organised crime, education is certainly one of the most relevant. Different papers have analysed the relationship between organised crime and education, highlighting the pernicious long-run effect of the former on human capital accumulation, a key determinant of economic growth and social welfare. Along this direction, [12] find that the presence of organised crime in Calabria inhibits the accumulation of human capital both directly (reducing the incentive to invest in formal education) and indirectly (increasing migration outflows). Using historical data on the spread of the Mafia in Sicily at the end of the 19th century, [1] find significant and quantitatively large negative impacts of the Mafia on literacy and high school completion rates.

More recently, [13] distinguish two different transmission channels through which the presence of mafia-type organizations can reduce economic returns to schooling, thus impairing human capital accumulation. Indeed, common to both the channels is the distortion of the economic incentives of the agents that occurs when organised crime alters (corrupts) the socio-economic fabric of a given territory: 1) the incentive of young people to acquire and supply education; and 2) the incentive of firms to demand highly educated personnel. According to the authors, the youngsters' beliefs on education versus crime largely depend on their assessment of the expected effort and payoff associated with each of the two options but are also influenced by a set of (social, cultural, human, etc.) values that permeate a certain community and that are transmitted by family, school and neighbourhood. The possibility to engage in crime to make "easy money" as well as the appeal, prestige and honour associated with the figure of the *Mafia* bosses and their affiliates stifle the (economic and otherwise) return of investment in education, prompting the youngsters either not to enrol in school or to

[1] On this matter, [19] confirm the strong correlation between the values received from parents and those that children, once grown up, have passed down to their descendants.

drop out prematurely or to exercise a sub-optimal level of school commitment (in terms of study effort, lesson attendance and compliance to rules).

Turning to the firms' side and incentives, [13] observe that the presence of *Mafia* at the local level drains resources from the high-tech economic sectors, where normally many highly educated workers are employed, towards labour-intensive and high cash-flow sectors of the (often shadow and illegal) local economy. This factor along with the related disincentives for firms to innovate where the environment is *Mafia*-like and competition between companies is reduced drive down the demand for high-skill/high-quality labour.

In connection with the above-mentioned literature, in this work, we embrace the hypotheses regarding the mechanisms through which organized crime impacts on the accumulation of human capital and, hence, on educational outcomes. Nonetheless, we recognize that there may be further mechanisms, mainly in terms of physical capital accumulation and general efficiency of the local education system, behind the impact of organized crime on educational performance.[2] We control for potential effects due to those mechanisms by means of fixed effects in the empirical analysis; a more direct and detailed examination of these effects is outside the scope of our paper.

2.2. Measuring organised crime

Notwithstanding the above-mentioned socio-economic effects of organised crime, attempts to measure its diffusion are quite scant. In fact, official statistics are often lacking and the number of complaints usually under-reports the real dimension of such phenomenon. Indeed, quantifying and understanding organised crime is an extraordinarily complex task, because of its vague, hidden, and multi-faceted nature that encompasses several dimensions, well beyond the sole identification of organised groups and the definition of the committed crimes [37]. Moreover, the lack of an agreed international definition [38–41] has made it even more difficult to develop accurate and rigorous quantitative and qualitative measures of the phenomenon to make reliable comparisons of crime trends and characteristics across countries. Therefore, to date, different measurement approaches followed by international and European organizations, either based on official recorded data[3] or on international surveys,[4] have each its own advantages and disadvantages and respond to specific purposes (see [42], for a detailed discussion).

Looking at the Italian case, data on single aspects of organised crime is routinely collected by the Italian National Institute of Statistics (ISTAT) in the *Territorial Information System on Italian Justice*.[5] This includes information on extortions, bomb attacks, arson and crimes of criminal association, crimes against property, thefts, and robberies, etc. Other data on organised crime are yearly provided by the Ministry of Interior as part of its institutional activity.

A concise index that is often used to map the infiltration of *Mafia*-type organizations at the provincial level in Italy is the one proposed by [15].[6] This index (*Indice di Presenza Mafiosa*, IPM[7]) uses data referring to the period 2000–2011 on the number of *Mafia* murders or attempted *Mafia* murders, persons charged with *Mafia* association (Decree Act 416bis), municipalities and public administrations whose councils have been dismissed because of *Mafia* infiltration (Legislative Decree 31/05/1991, n. 164), assets seized and confiscated to organised crime, active criminal groups described by DIA and DNA[8] reports. The IPM is then normalised, with values ranging from 0 (minimum) to 1 (maximum).[9]

Fig. 1 depicts the distribution of IPM values across Italian provinces[10]. With few exceptions (e.g., Genova, Roma and Torino), the figure shows that the Southern provinces of Italy are the most badly affected by *Mafia*-type phenomena. Specifically, Napoli is the province with the highest IPM value, followed by Reggio Calabria, Vibo Valentia and Palermo. This is in line with the strong presence of *Mafia*-related organizations in traditionally controlled Southern regions such as Campania (*Camorra*), Apulia (*Sacra Corona Unita*), Calabria ('*Ndrangheta*) and Sicily (*Cosa Nostra*).[11]

Consistently with the geographical divide of the mafia presence in the society that emerges from Fig. 1, we decide to focus our analysis on the relationship between organised crime and educational outcomes in the Southern regions of Italy, where the *Mafia* values are historically more rooted in the society. Restricting the field of the analysis to Southern Italy also allows us to implement an IV strategy. In this regard, to further validate the robustness of our results, we consider a measure of organised crime alternative to IPM, which aims to capture a narrower manifestation of the phenomenon, namely its ability to penetrate local institutions. Specifically, we look at the Italian policy imposing the dismissal of local administrations whenever they are suspected of Mafia infiltration.[12] Indeed, information on the municipal councils dismissed because of suspected mafia infiltration is already included in the IPM index, being one of its five core indicators. However, despite the same source of data, our index of *Mafia* institutional infiltration (IIM) is computed in a slightly different way from that included in the IPM[13]: it is

[2] [11] study the effect of missing resources, due to corruption, on educational outcome of primary school students in Brazil and find a significant negative association between corruption and school performance of primary school students.

[3] See, for example, Statistics on Crime Trends and the Operations of Criminal Justice Systems collected by the United Nations Office on Drugs and Crime, the Eurostat Crime and Criminal Justice Statistics.

[4] Among the others, the World Economic Forum annual survey on obstacles to businesses; the Merchant International Group on countries' investment risks, the PricewaterhouseCoopers Global Economic Crime Survey, the Kroll Global Fraud Survey, the Ernst and Young's Global Fraud Survey.

[5] To this purpose, ISTAT has adopted the operational definition of organised crime as used by the Italian Ministry of the Internal Affairs, which includes mafia murders, attacks, arsons, serious robberies (e.g., bank. post offices, conveyors of bank and postal values, etc).

[6] Transcrime is the joint research Centre of the Catholic University of the Sacred Heart, the University of Bologna and the University of Perugia.

[7] The IPM is part of a more complex composite index of territorial risk of organised crime infiltration at the provincial level (*Indice di Rischio Territoriale*, RT) developed by [15].

[8] DIA is the Italian Anti-*Mafia* Investigations Directorate, whereas DNA is the National Anti-*Mafia* and Anti-terrorism Directorate.

[9] More specifically, in this paper, the index is normalised to 1 to make the values of the 107 provinces more homogeneous, assigning 107 points to the first province for IPM, 106 to second and so on. The scores are then recalculated by attributing 1 to the first province and 0 to the last.

[10] In Fig. 1 the Italian Regions belonging to the ISTAT (Italian Institute of Statistics) SOUTH classification are bordered in red while those belonging to the CENTER classification are bordered in orange. Regions classified as NORTH are not bordered.

[11] These Italian regions are highlighted in Fig. 2.

[12] The beneficial (direct and indirect) effects of municipal councils' dismission on local politics and other socio-economic factors have been empirically analysed by many works (among others, [36,43]). [44] find that local governments' dismissals are associated to a persistent fall of petty crimes (e.g., thefts) but have little consequences on offenses more closely related to the activity of organized crime (e.g., homicide, extortion, drug trafficking, etc.).

[13] In the construction of the IPM index, the number of municipal councils dissolved because of suspected mafia infiltration was divided by the number of municipal councils of a given province, which could potentially be dissolved. The values are then normalised, to facilitate comparisons.

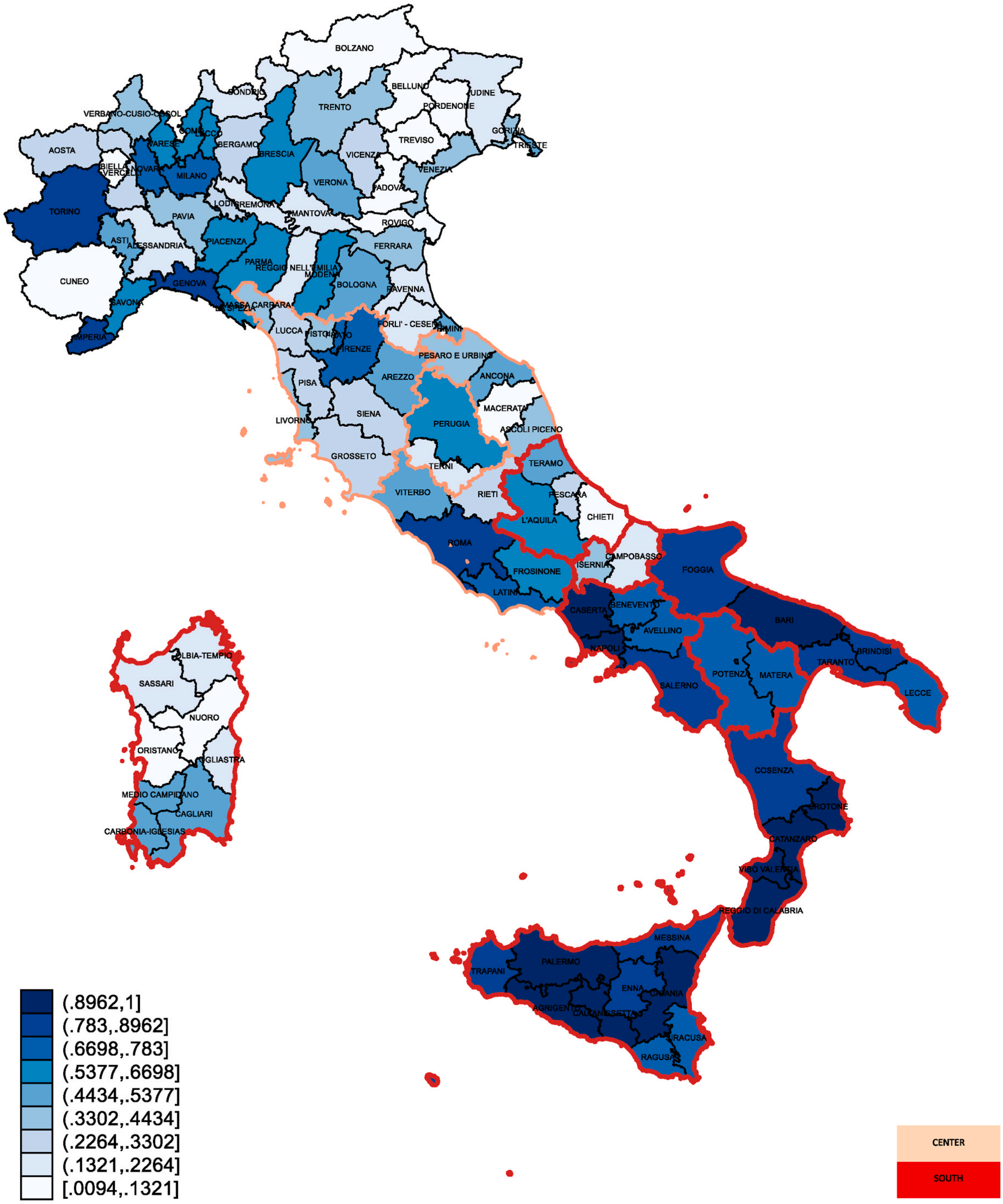

Fig. 1. IPM index at provincial level.
Note: Map displays the index IPM (*Indice di Presenza Mafiosa*) of the infiltration of *Mafia*-type organizations at provincial level in Italy from 2000 to 2011, as computed by [15]. The index is normalised to the scale 0–1 according to a min-max criterion, where 1 = the highest value in the 107 provinces. Regions belonging to the ISTAT (Italian Institute of Statistics) SOUTH classification are bordered in red while those belonging to the CENTER classification are bordered in orange. Regions classified as NORTH are not bordered.
Source: our elaboration on data provided by [15].

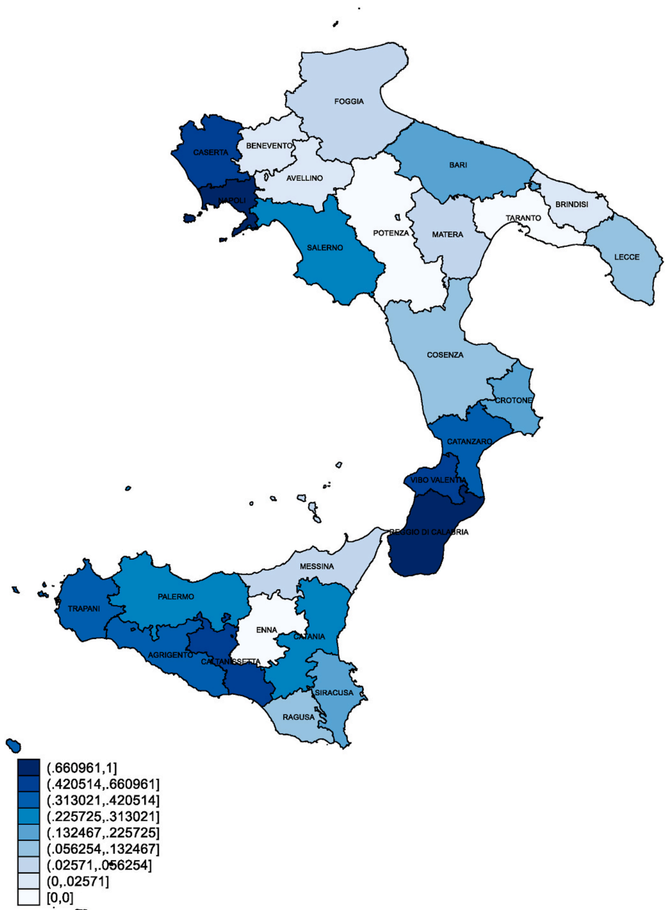

Fig. 2. Organised crime institutional infiltration (IIM) at provincial level in the Southern regions with an historical presence of organised crime.
Note: Map displays the index of *Mafia* institutional infiltration (IIM) computed as the ratio between the population of municipalities whose councils have been dismissed because of mafia infiltration (Legislative Decree n. 164/91) from 1991 to 2011 and the total population of the province. The index is normalised to the scale 0–1 according to a min-max criterion, where 1 = the highest value in the 107 provinces.
Source: our elaboration on data provided by Italian Ministry of Internal Affairs.

the ratio between the population of municipalities whose councils have been dismissed because of *Mafia* infiltration (Legislative Decree n. 164/91) in the period 1991 to 2011 and the total population of the province.[14] To this end, Fig. 2 shows the distribution of IIM index in the Southern Italian regions where the phenomenon of mafia-type criminal organizations is historically more widespread. Compared to the previous Fig. 1, here the phenomenon appears to be less homogeneously distributed in the South of the country, with few provinces (e.g., Potenza, Taranto, and Enna) even showing very low IIM values. As already explained, we use our IIM index as robustness check of our results on the relationship between organized crime (as measured by the key indicator IPM) and educational outcomes in Southern Italy.

3. The geographical divide in educational outcomes in Italian compulsory schools

The implementation of a national evaluation service of students' achievements in the Italian compulsory education system[15] has been long and troublesome. It can be traced back to the end of 1990 (Legislative Decree n. 258/1999), when the reform that granted school autonomy also led to the establishment of the National Institute for the Evaluation of the Education and Training System (hereafter, INVALSI).[16] Since then, a large body of empirical research has been devoted to the identification of the core determinants of the INVALSI test scores in Italy, distinguishing between students', family, school, classmates (peers) and context characteristics.[17]

For the purposes of our analysis, a widely debated issue is related to the existence of a large 'geographical learning gap' in the INVALSI

[14] To avoid the risk of the index taking values above 1, the city councils that have been dismissed more than one time during the period 2000 to 2011 are counted just once. Furthermore, the index is normalised to the scale 0–1 according to a min-max criterion, where 1 = the highest value in the 107 provinces.

[15] For a snapshot of the Italian education system, see Appendix A.1.

[16] For a concise description of the INVALSI assessment system, see Appendix A.1.

[17] Applying multilevel linear models, existing literature on individual and peer effects focuses on socio-economic status, gender, and ethnic differences. Thus, evidence is found of gender (favouring males in mathematics achievements) as well as immigrant (i.e., 1st and 2nd generation)/native achievement gaps [45–47]. It has also emerged that the proportion of early enrolees in the classroom has a positive impact on average student's achievements [48]. School characteristics have been primarily studied looking at the effect of school/class body composition [49], school size, managerial practices, and characteristics of school principals (e.g., [50]). Overall, class effects on student achievements have been found to be larger than school ones [51].

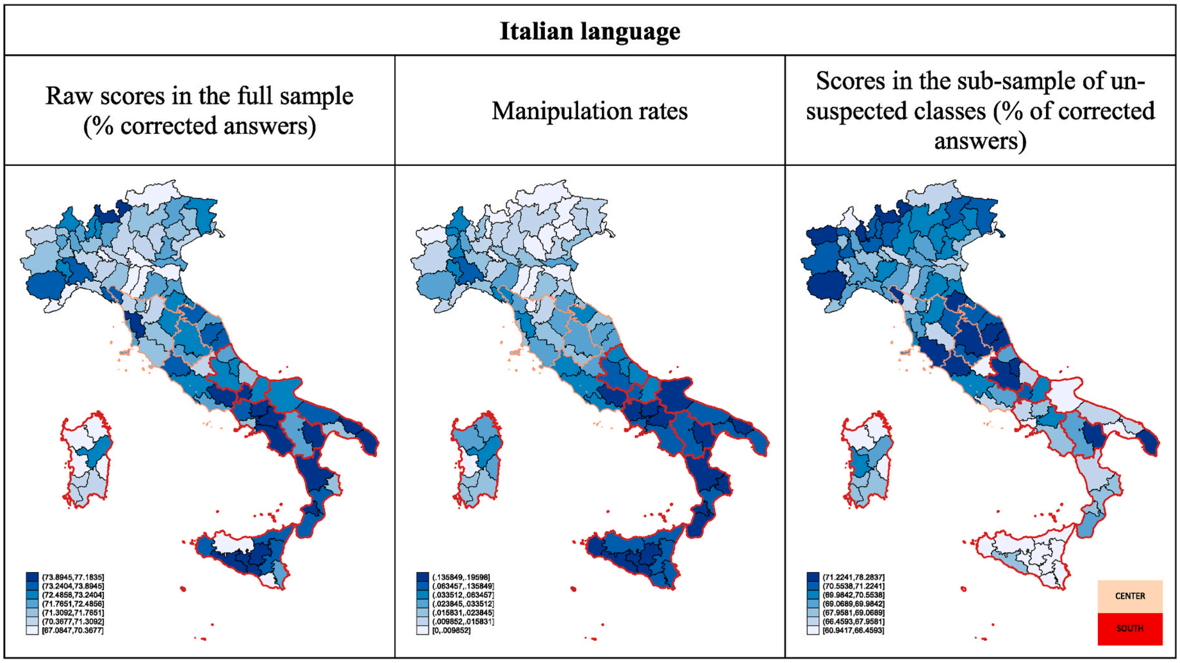

Fig. 3. Class scores in Italian language and manipulation rates (at provincial level).
Note: Map displays the class scores in Italian language and manipulation rates at provincial level [26]. Regions belonging to the ISTAT (Italian Institute of Statistics) SOUTH classification are bordered in red while those belonging to the CENTER classification are bordered in orange. Regions classified as NORTH are not bordered.
Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

student achievements. As it can be seen by the left-hand side panels of Fig. 3 and 4,[18] the two distributions of the raw (observed) scores[19] in Italian language and mathematics at provincial level for the school years 2009-11 provide a similar and quite counterintuitive picture: second and fifth grade students in the South of Italy outperform those in the North. This geographical gradient seems highly unreliable in the light of the very much convergent regional patterns emerging from the Programme for International Student Assessment (OECD-PISA) (among others: [52,53]) and other international surveys[20] [54,55]. Furthermore, the fact that Southern students perform better than Northern ones is in contrast with the marked backwardness of the South of Italy along many socio-economic indicators (e.g., unemployment rate, per-capita income, labour productivity, quality of governance and civic life indices, etc.) and the well-established literature on the direction of correlation between main predictors and student achievements [56].

The above problem has been widely discussed in the literature [57] and several explanations have been proposed for it, including a higher motivation for Southern students when compiling the test [71] and diverging grading standards among macro-regions [58]. However, the most credible and agreed explanation for reconciling geographical patterns emerging from test surveys in Italy relays on the differences existing in the administration of tests. In the case of the INVALSI tests, the reliance on local single teachers (as compared to teams of teachers in TIMSS and PIRLS) is likely to give rise to opportunistic behaviours by both teachers and students. Score manipulation can take the form of either conventional cheating (by both students and teachers) or teachers' shirking in score transcription [59].[21] Indeed, manipulation of INVALSI test scores has proved to be considerably more widespread in the South and the Islands [26,56], being also correlated with measures of social capital [61].

To deal with these opportunistic behaviours, since 2009 INVALSI has adopted two different strategies. First, external inspectors are sent every year to a random and representative sample of classes to monitor the test administration and the marks reporting process. In this regard, using a natural experiment, [62] show that the introduction of external examiners has negative effects on test performance, both direct (comparison between monitored and un-monitored classes within the same school) and indirect (comparison of un-monitored classes in schools with and without external examiners), ranging between 4.3% and 6.6% and between 1.2% and 1.9%, respectively.

The second strategy adopted by INVALSI consists in improving the accuracy of data by recalculating the test scores based on the probability that cheating occurs in each classroom during the test. To this purpose, a subject-specific index (Cheating Propensity Indicator, CPI) has been built according to which a class is considered at higher risk of cheating (i.e., "suspicious") the more homogeneous is the answer behaviour for each item of the subject, the lower is the percentage of missing data, the

[18] In Figs. 3 and 4 the Italian Regions belonging to the ISTAT (Italian Institute of Statistics) SOUTH classification are bordered in red while those belonging to the CENTER classification are bordered in orange. Regions classified as NORTH are not bordered.

[19] The scores have been standardised into a range [0;100] that represents the percentage of right answers to the questions of the test.

[20] Other international surveys largely employed in the Italian literature on educational outcomes include the Trends in International Mathematics and Science Study (TIMSS) and the Progress in International Reading Literacy Study (PIRLS), which are both conducted by [54]. The former takes place every four years in 60 countries to measure mathematics and science achievements of fourth and eighth grade students. The latter is generally targeted to fourth graders to assess, every five years, students' reading achievements.

[21] [60] distinguish between many forms of opportunistic behaviours by teachers during and after the test administration. Thus, teachers may adopt a benevolent attitude by providing discretionary help to some students (generally, the lower performing ones) or lowering monitoring intensity and letting them interact and collaborate. Once the test has been compiled by the students, teachers may also deliberately alter or even change student responses on answer sheets. The authors find significant social multiplier effects in student cheating, resulting from students' interactions in presence of teachers' tolerating behaviours.

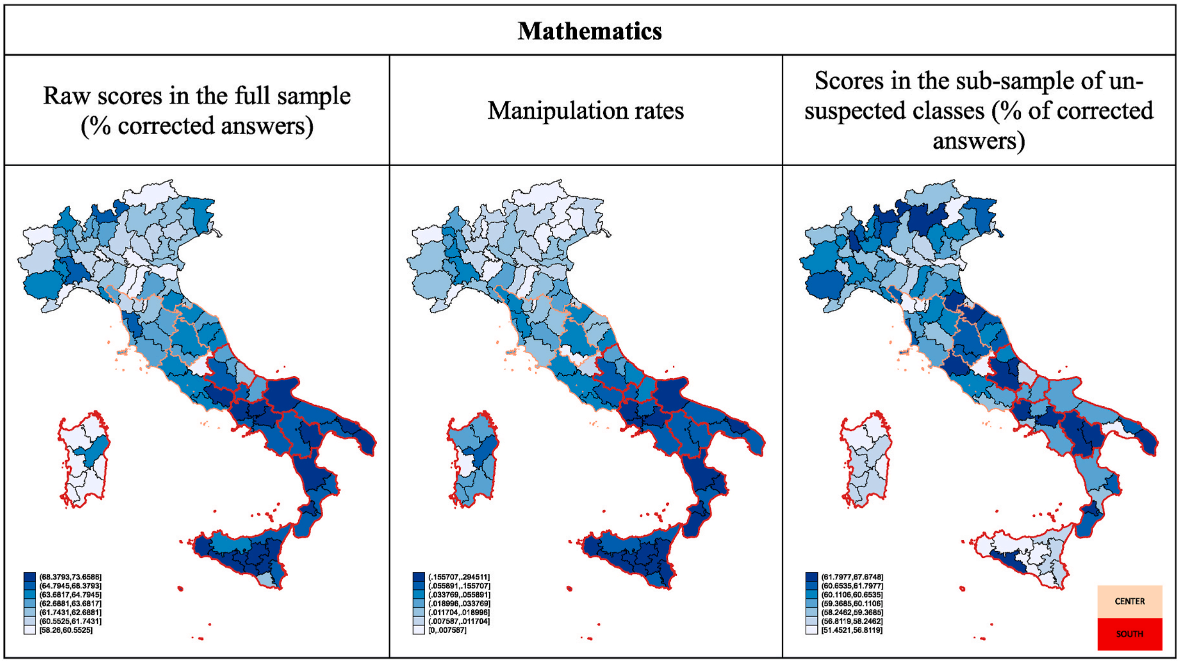

Fig. 4. Class scores in Mathematics and manipulation rates (at provincial level).
Note: Map displays the class scores in Mathematics and manipulation rates at provincial level [26]. Regions belonging to the ISTAT (Italian Institute of Statistics) SOUTH classification are bordered in red while those belonging to the CENTER classification are bordered in orange. Regions classified as NORTH are not bordered.
Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

higher is the average score, and the more close to zero is the within-class variability of the final score.[22]

The correction made by INVALSI to adjust for manipulation is, however, only able to affect marginally the geographical patterns emerging from raw scores [56]. More specifically, [56] attempt to unravel true geographical patterns of INVALSI score data by constructing a manipulation index that replicates the CPI employed by INVALSI but replaces fuzzy clustering with hard clustering methods. This allows computing a binary variable to detect class outliers and to derive bounds for the average test scores net of manipulation. These bounds are found to be tight enough to reverse the evidence from raw score data for both Italian language and mathematics.

Therefore, a recent stream of literature has tried to develop statistical algorithms other and more sophisticated than the CPI used by INVALSI to detect cheating behaviours and correct observed test scores. Using a Maimonides-style instrumental variables (IV) approach [63], [26] estimate the effects of class size on INVALSI achievements, finding larger returns to class reductions in Southern Italy. However, these effects disappear after controlling for score manipulation (mostly in the form of teachers' shirking), which is more likely to occur in smaller classes. To measure manipulation, the authors develop a specific indicator based on evidence of implausible score levels of students in a class, a doubtful within-class average, an unlikely small dispersion of test scores, an unusually low proportion of missing items and a high concentration in response patterns (as measured by the Herfindahl index). The indicator is like the CPI employed by INVALSI but generates a dummy (=1 for classes where score manipulation seems likely and 0 otherwise) instead of a continuous variable. The pictures emerging from the use of this dummy at provincial level for manipulation rates in Italian language and Mathematics are depicted in the central panels of Figs. 3 and 4, respectively. They show a marked presence of manipulation especially in the Southern areas of the country and, thus, corroborate the hypothesis of opportunistic behaviours playing a relevant role in explaining the geographical distribution of uncorrected scores. Indeed, by restricting the analysis only to non-suspicious classes according to the procedures followed by [26]; the right-hand side panels of Figs. 3 and 4 show that the regional gradient reverse for scores in Italian language but not for those in Mathematics.[23] This result has influenced the choice of our dataset, which focuses mainly on Italian language achievements. Nonetheless, in what follows, we find quite comparable results also employing Math scores.[24]

4. Data

Our dataset has been built from different sources and relates to three macro categories: educational outcomes in elementary schools (second and fifth grade students) in the 2009-11 academic school years; indices of organised crime at local level; variables used in our IV strategy.

4.1. Data on educational outcomes

To evaluate students' achievements, we use a dataset similar to that employed by [26].[25] Accordingly, data refer to INVALSI tests for Italian language and math in elementary schools (second and fifth grade

[22] For further details on the construction of the CPI index and the 'fuzzy clustering approach' see [53].

[23] Cheating and score manipulation is found to be more relevant in Math than in Italian (Battistin et al., 2014; [26,60]. This is mainly due to the structure of the INVALSI text, whereby closed answers and short logic problems are proposed in Math, while text comprehension and interpretation are required in Italian language [60]. Therefore, the reliability of the manipulation correction is lower for Math scores than for Italian ones.

[24] To derive statistical bounds on the distribution of math scores of elementary school students in Italy correcting for cheating, see [56].

[25] Available online at the following link, https://www.aeaweb.org/articles?id=10.1257/app.20160267&&from=f.

Table 1
Descriptive statistics of educational outcomes and score manipulation index by geographical macro-area.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Whole Italian sample					
ANSWERS_ITAL_PCT	140,010	72.0772	10.1722	20.9790	100.0000
ANSWERS_ITAL_STD	140,010	0.0100	0.5226	−3.0167	1.8039
CHEAT_ITAL	140,003	0.0553	0.2286	0.0000	1.0000
Subsample by geographical macro-area					
North					
ANSWERS_ITAL_PCT	61,938	71.4879	8.4254	24.8869	100.0000
ANSWERS_ITAL_STD	61,938	−0.0226	0.4074	−2.0187	1.7214
CHEAT_ITAL	61,936	0.0148	0.1206	0.0000	1.0000
Centre					
ANSWERS_ITAL_PCT	25,560	72.5024	9.3896	26.9231	100.0000
ANSWERS_ITAL_STD	25,560	0.0386	0.4726	−2.2027	1.8039
CHEAT_ITAL	25,557	0.0416	0.1996	0.0000	1.0000
South					
ANSWERS_ITAL_PCT	52,512	72.5653	12.1865	20.9790	100.0000
ANSWERS_ITAL_STD	52,512	0.0346	0.6491	−3.0167	1.7865
CHEAT_ITAL	52,510	0.1099	0.3128	0.0000	1.0000

Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

Table 2
Educational outcomes in the subsample of not "suspicious" classes by geographical macro-area.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Italy					
ANSWERS_ITAL_PCT	132,256	70.9396	9.2336	20.9790	99.2823
ANSWERS_ITAL_STD	132,256	−0.0545	0.4593	−3.0167	1.7447
North					
ANSWERS_ITAL_PCT	24,495	71.6777	8.6624	26.9231	96.7213
ANSWERS_ITAL_STD	24,495	−0.0079	0.4231	−2.2027	1.5864
Centre					
ANSWERS_ITAL_PCT	61,022	71.1982	8.1373	24.8869	97.8395
ANSWERS_ITAL_STD	61,022	−0.0389	0.3871	−2.0187	1.5077
South					
ANSWERS_ITAL_PCT	46,739	70.2151	10.7044	20.9790	99.2823
ANSWERS_ITAL_STD	46,739	−0.0992	0.5514	−3.0167	1.7447

Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

students) in the 2009-11 academic school years.[26]

In our empirical analysis, we use data at class-level. Applying the same restrictions as in [26],[27] the final sample comprises 140,010 classes. Our raw educational outcome variable is the average class percentage of corrected answers in Italian language (ANSWERS_ITAL_PCT). The variable is also standardised by grade and year of survey to have a mean of zero and a unit variance (ANSWERS_ITAL_STD), thus making OLS estimator unbiased. To account for score manipulation, we employ the dummy variable developed by [26]; indicating classes where score manipulation seems likely (CHEAT_ITAL = 1 for a "suspected" class and 0 otherwise).[28]

Table 1 reports descriptive statistics for our educational outcome variables and the index of score manipulation by geographical macro-area. The highest raw average scores in Italian language are in the Southern classes, where, however, dispersion in values is very high. As for score manipulation, Table 1 shows that, on average, around 5.5% of classes are flagged as "suspicious". Manipulation rates, however, varies greatly throughout the country, reaching a minimum in the North (around 1.5% of classes) and a maximum in the South (around 11% of classes). Hence, the phenomenon seems to be more concentrated right there where the observed achievements in Italian language appear to be higher.

In Table 2, the analysis on educational outcomes has been restrained to the subsample of non "suspicious" classes for score manipulation. Looking at the three macro-areas the previous picture reverses: best scores are now achieved by the Northern classes while the worst scores are those gained by the Southern ones.

Table 3
Descriptive statistics of IPM index by geographical macro-area.

Macro-area	Mean	Std. Dev.	Min	Max
Italy	0.6273	0.2903	0.0094	1.0000
North	0.4708	0.2589	0.0094	0.8585
Centre	0.6171	0.2462	0.1132	0.8868
South	0.8167	0.2266	0.0189	1.0000

Source: our elaboration on data provided by the Italian Ministry of Internal Affairs and [15].

4.2. Data on organised crime at local level

As main measure of organised crime, in this paper we use the IPM index developed by [15] to map the presence of mafia-type organizations on the Italian territory. Therefore, we refer to the previous section 2.2 for a brief description of the index. Here, we only point out that the IPM data refer to the period 2000–2011.

Table 3 provides the descriptive statistics of the IPM index for Italy as a whole and by geographical macro-area. Overall, some points are worth noting. First, looking at the entire Italian territory, the index shows an extremely high dispersion of values. Considering the three macro-areas, as expected, moving from the North to the South of the country, a clear geographical gradient appears. Notwithstanding the lower average values, the Northern part of Italy is not completely immune to the risk of criminal infiltration. However, the emerging picture across the Northern provinces is quite homogeneous (the standard variation is always well below the national average). On the contrary, in the South of the country, the phenomenon of organized crime, as might be expected, is more prominent and the index has a higher average value than in other areas of the country.

Based on this evidence, our analysis of the relationship between organised crime and educational outcomes focuses on Southern Italy where the presence of *Mafia*-type organizations is traditionally more widespread and rooted in the society. As mentioned above, to assess the relationship between educational outcomes and the presence of organised crime, we employ a second index (IIM) in addition to the IPM index.[29]. This index proxies a narrower phenomenon of crime organization, namely its ability to penetrate local institutions to influence their decision-making processes and, ultimately, their activities. Once again, for the description of how the IIM index is constructed we refer to the previous section 2.2, where the reference period of the data is also specified.

4.3. IV variables

In our IV analysis, we employ two instruments based on historical

[26] The choice to neglect test achievements in Mathematics is due to the previously discussed evidence concerning the effects of the manipulation correction. However, results for mathematics, are often provided in the text (or in the Appendix) alongside those for Italian language. If not, they can be requested from the authors.

[27] The applied restrictions concern class and school size, and the exclusion of classes in private schools. For further details, see [26].

[28] When using the cheating variable our initial sample is further restricted to 140,003 classes.

[29] The descriptive statistics for the index IIM are reported in Table A.2.2 in Appendix A.2.

variables. Both are computed at the provincial level and available only for the Southern Italian regions. Specifically, we employ, as instruments, the diffusion of *Mafia* organizations at the end of 19th century (MAFIA_HIST) at the provincial level, provided by [32], and the land productivity (LANDPROD) measured by the total value of land tax per square kilometres at provincial level, taken from [29]. We discuss the validity of these instruments in Section 6.2.

5. Preliminary findings on the whole Italian sample

5.1. Setting the stage

In our opinion, the choice of adopting the data and the empirical approach provided by [26] has relevant advantages. First, due to its adoption in the literature it would be easier to draw some comparative results with the previous works. Second, we can run our empirical exercise on the role of organised crime of class achievement by reducing the potential risks of omitted variable bias and measurement errors.

However, contrary to [26], we are not interested in understanding the effects of class size on test achievements. Therefore, in this paper we employ a slightly different and simpler model specification, which, after controlling for several factors, assesses whether the class achievement in Italian language in each province is associated to the presence of organised crime into the institutions of that province. To this purpose, through the school code, each class score is linked to the province where the school is located.

Nevertheless, in our model, we employ a full set of controls at class, school and geographical level as in [26]. More specifically, to control for score cheating and manipulation, we include both the manipulation dummy (CHEAT_ITAL) and a variable indicating the presence of randomly assigned external monitors (MONITORED = 1 if the class is selected for monitoring and 0 otherwise).[30] The other control variables are dummies for the geographic macro-area location of the class (CENTRE, NORTH and SOUTH), the number of students enrolled in the grade at school (STUDENTS), the class size (CLSIZE), the proportion of female students in the class (FEMALE), the proportion of immigrant students (IMMIGRANTS_BROAD), the proportions of students whose father is a high school dropout (DAD_LOWEDU) or a high school graduate (DAD_MIDEDU) or a college graduate (DAD_HIGHEDU), the proportions of students whose mother is unemployed (MOM_UNEMP) or a housewife (MOM_HOUSEW) or employed (MOM_EMPLOYED), and variables for missing values of these categories. Stratification controls include the year of the survey, the class grade, and the region in which the class is located. Finally, we use standard errors clustered at both school and grade level for all estimates. A description of all the covariates employed in the models is provided in Table A2.1 in Appendix A.2.

Before estimating our model, we conduct a preliminary exploratory analysis of our class data. Fig. 5 graphs the kernel density distributions of unstandardised (i.e., top panels) and standardized (i.e., bottom panels) class scores by geographical macro-area. These are obtained by pooling together score data on second and fifth grade classes for the school years 2009–2011. Looking at the two distributions on the left-hand side where class scores are not corrected for manipulation, those geographic patterns concerning the average class scores and score dispersion are clearly visible. Once data are corrected for manipulation (by excluding the “suspicious” classes) (i.e., distributions in the right-hand side) the kernel pictures become like those already described in Table 2. In details, the score distributions of the Southern macro-area shift to the left, and the shape of their right tails starts resembling that of the distributions by the other macro-areas. Consequently, the mean values of the score distributions of the Southern macro-area decrease with respect to the other two macro-areas.

However, the high heterogeneity of the Southern regions in their manipulation behaviours (as illustrated in the middle panels of Figs. 3 and 4) poses some relevant questions. Specifically, we question whether poor class achievement in the South of Italy is due to a geographic problem or to some ‘environmental’ factors (i.e., the presence of organised crime in the society) that are geographically distributed and likely to lower the expected returns to investment in education. Under the latter hypothesis, the geographic factor would act as a mere confounding in analysing the relationship between organised crime and educational outcomes.

To shed a light on this issue, in Fig. 6 we replicate the previous kernel distributions of class scores but by the level (low, middle, and high) of the IPM variable. It is worth noting that the corresponding kernel estimates in Figs. 5 and 6 provide almost overlapping graphs, thus supporting our hypothesis on the role played by the presence of organised crime (mafia-type organizations) at local level in explaining the educational outcomes.

5.2. Preliminary findings

As a first (preliminary) test of our hypothesis concerning the relationship between the presence of organised crime within the local society and the INVALSI outcomes achieved by primary school students, we employ the full set of information on classes located in all Italian regions. Hence, we consider the following linear model:

$$y_{i,g,k,j,t} = \alpha + \beta_1 AREA_j + \beta_2 IPM_j + \beta_3 SCHOOL_{i,j,t} + \beta_4 CLASS_{i,g,k,j,t} + \beta_5 FIXED_{EF\,i,g,k,j,t} + \varepsilon_{i,g,k,j,t} \tag{1}$$

where $y_{i,g,k,j,t}$ is the outcome score in class i in grade g at school k in province j in year t, AREA is a categorical variable indicating the three Italian macro-areas (South is used as reference category) and IPM is our variable measuring the presence of organised crime into the society at provincial level. The model also controls for a set of variables at SCHOOL and CLASS level (including the manipulation dummy), which have been previously discussed. Fixed effects (FIXED_EF) for grade, survey year and region are also included to capture specific unobservable factors that may affect the individual outcome.[31] Standard errors clustered at both school and grade level are used for all estimates.

Looking at Eq. (1), conventional picture predicts that, after controlling for manipulation, $\beta_1 > 0$, meaning that the geographical factor matters in explaining test achievements (i.e., the North and Centre outperform the South). The specific hypothesis that we want to test in this paper is that the organised crime matters, too (i.e., $\beta_2 < 0$).

Table 4 reports OLS estimates for different specifications of Eq. (1), using, as dependent variable, the standardized INVALSI scores. For the reasons previously explained, we focus on the (standardized) scores in Italian language (columns 1–3), but the table also reports those (standardized) in math (columns 4–6). Therefore, in the following we comment only the former, leaving the reader to verify the consistency of the results with the latter. In columns 1 and 4, we include macro-area controls only. After controlling for “suspicious” classes, the estimation results confirm the existence of “geographical” patterns, with higher performances in the North and in the Centre (the two coefficients are positive and highly statistically significant) compared to the South of the country. In columns 2 and 5, we test the alternative specification where the IPM index at provincial level is included in the model, but the geographical variables are excluded. As expected, the sign of the IPM variable is negative and highly significant (at the 1% level). In columns 3 and 6, the AREA variables along with the IPM index have been included

[30] Unlike the paper by [26]; in our model we do not employ class size cut-offs based on Maimonides’ Rule.

[31] For an estimate of model (1) for the (standardized) scores in Italian language without regional fixed effects, see Table A.3.1 in Appendix A.3. Estimates for mathematics are available from the authors upon request.

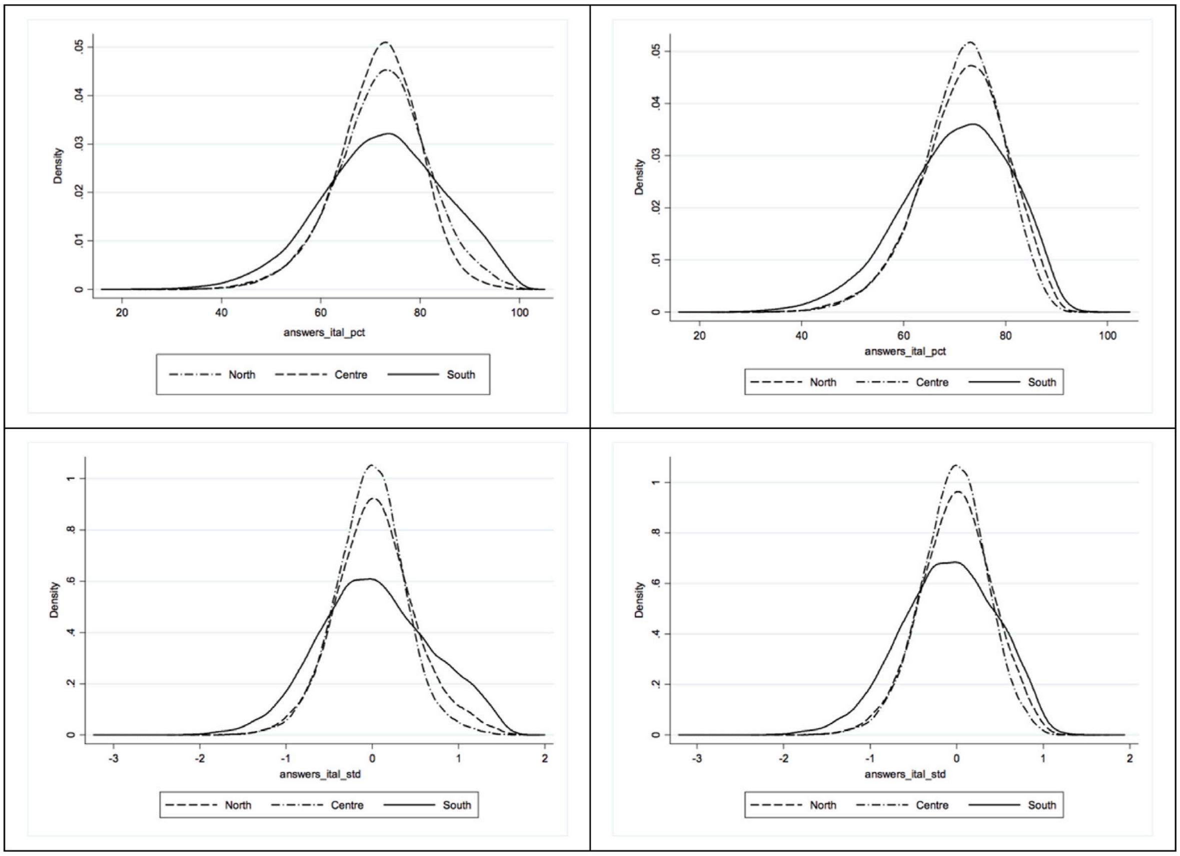

Fig. 5. Kernel density estimates of unstandardised (top) and standardised (bottom) class scores in Italian language by geographical macro-area (left: without correction for score manipulation; right: with correction for score manipulation).
Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

in the model to check whether the effects emerging from the previous two specifications should be regarded or not as two sides of the same coin. As shown in Table 4, both the geographical variables and the crime indicator continue to be highly statistically significant (at the 1% level) and with the correct signs, thus providing support that they are capturing different phenomena and telling us different stories.

The estimated IPM coefficient is very stable across specifications. Using the specifications in columns 2 and 3 of Table 4, one standard deviation increase in the IPM index (equivalent to 0.2903, see Table A.2.1 in Appendix A.2) is associated with a reduction in educational outcomes of 0.0278 (0.2903 × 0.0956), equivalent to about a twentieth of the standard deviation of class achievement. This effect seems somewhat small, although it is equivalent to almost half of the relative impact of geographical areas on the average class achievement. In fact, using the most conservative specification in column 3, one standard deviation increase in the variable NORTH is associated with an increase in class achievement of 0.0487, compared to the SOUTH.[32] Finally, the impacts of the IPM index on educational outcomes are overlapping for math scores.

6. A focus on the Southern Italian school system

6.1. Baseline estimates

In this Section, we restrict the analysis to a subsample of classes located in Southern regions that have been historically characterised by a high presence of *Mafia*-type organizations. Therefore, we leave aside the North-South divide in educational achievements, and we focus on explaining the existing variability in educational outcomes among Southern classes. By doing so, we control for the effect of omitted characteristics that could potentially affect educational performance. While considering only the South of Italy, there are still large differences in the presence of organised crime at the local level (previous Figs. 1 and 2).

Before focusing on the South of Italy, we compare the educational outcomes achieved by classes located in regions with an historical presence of organised crime with the performance of classes located in regions without an historical presence of organised crime,[33] respectively, by estimating the following specification:

$$y_{i,g,k,j,t} = \alpha + \beta_1 HM\_REGIONS_j + \beta_2 IPM_j + \beta_3 SCHOOL_{i,j,t} + \beta_4 CLASS_{i,g,k,j,t} + \beta_5 FIXED_{EF\,i,g,k,j,t} + \varepsilon_{i,g,k,j,t} \quad (2)$$

where $y_{i,g,k,j,t}$ is the average outcome score in class i in grade g at school k in province j in year t, *HM_REGIONS* is a dummy equal to 1 for Sicily, Calabria and Campania, and equal to 0 for all other regions, IPM is our

[32] For the sake of clarity, we do not report the coefficient estimates of the other control variables in equation (1) throughout the paper. Overall, the estimates are coherent with the findings from previous studies. The full estimates are available from the authors upon request. Some robustness checks for the estimates on the whole Italian sample are provided in Appendix A.3.

[33] Two other regions in the South, Apulia, and Basilicata, have also witnessed the presence of criminal organizations since the mid-1970s [4].

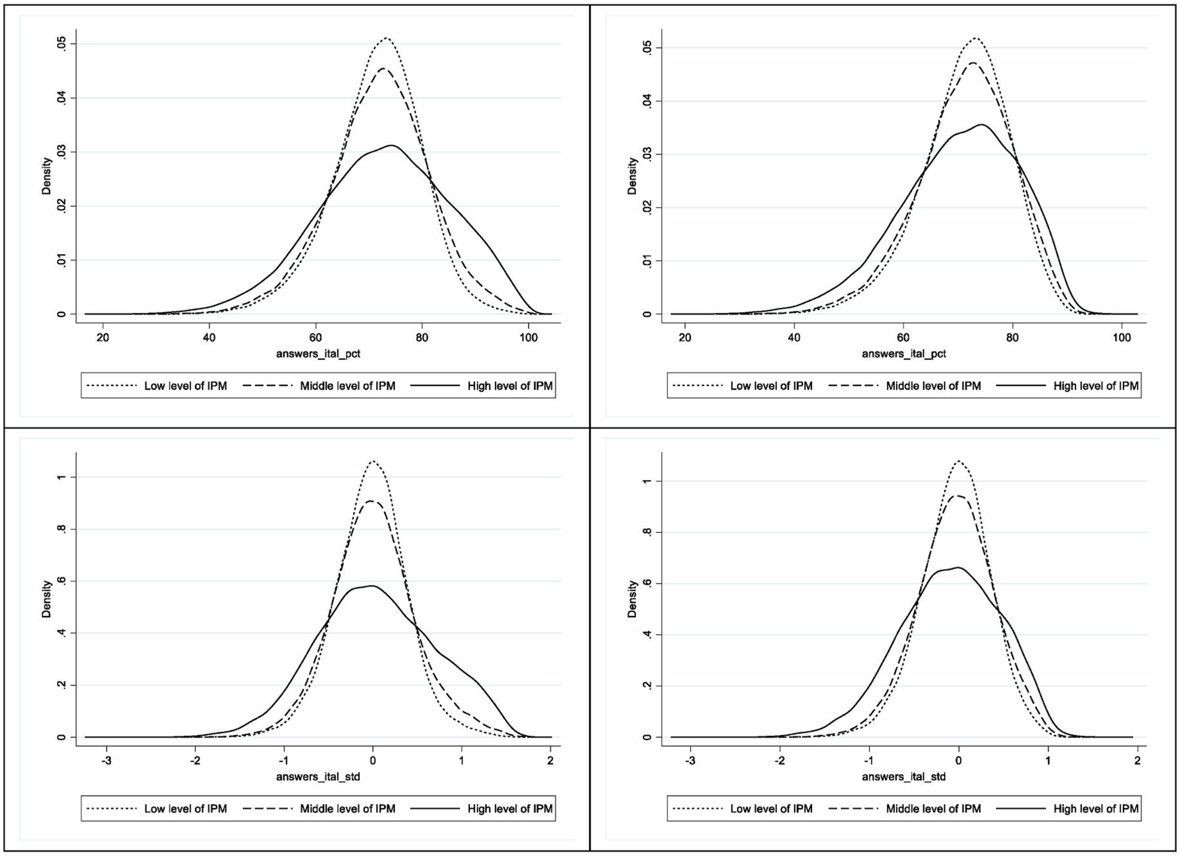

Fig. 6. Kernel density estimates of unstandardised (top) and standardised (bottom) class scores Italian language by level of IPM (left: without correction for score manipulation; right: with correction for score manipulation).
Source: our elaboration on data provided by [26] by pooling second and fifth grade students for the school years 2009–2011.

Table 4
OLS results on the full sample (dependent variable: standardized INVALSI scores).

Variables	Dependent variable					
	Standardised Italian language scores			Standardised math scores		
	(1)	(2)	(3)	(4)	(5)	(6)
NORTH	0.1063***		0.1260***	0.0698***		0.0902***
	(0.0157)		(0.0160)	(0.0214)		(0.0217)
CENTRE	0.0732***		0.0671***	0.0123		0.0060
	(0.0117)		(0.0119)	(0.0117)		(0.0163)
IPM		−0.0956***	−0.0956***		−0.0991***	−0.0991***
		(0.0090)	(0.0090)		(0.0116)	(0.0116)
Full set of other controls	yes	yes	yes	yes	yes	yes
Control for grade	yes	yes	yes	yes	yes	yes
Control for survey year	yes	yes	yes	yes	yes	yes
Control for region	yes	yes	yes	yes	yes	yes
Observations	140,003	140,003	140,003	139,996	139,996	139,996
R-squared	0.3313	0.3322	0.3322	0.3469	0.3475	0.3475

Note: The table reports OLS estimates. The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for GRADE, SURVEY_YEAR and REGION are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.
Source: our elaboration on data provided by Ministry of Internal Affairs and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

variable measuring the presence of organised crime at the provincial level. The model also controls for a set of variables at SCHOOL and CLASS level (including the manipulation dummy), which have been previously discussed. Fixed effects (FIXED_EF) for grade, survey year and region are also included.[34] Once again, Table 5 shows that the coefficient of IPM is highly significant and with the expected sign. The

[34] For an estimate of model (2) for the (standardized) scores in Italian language without regional fixed effects, see Table A.3.2 in Appendix A.3. Estimates for mathematics are available from the authors upon request.

Table 5
OLS results on the full sample – adding controls for regions with an historical presence of organised crime (dependent variable: standardised INVALSI score).

Variables	Dependent variable			
	Standardised Italian language score		Standardised math score	
IPM		−0.0956***		−0.0848***
		(0.0090)		(0.0123)
HM_REGIONS	−0.0057*	0.0051	−0.0049	0.0050
	(0.0031)	(0.0145)	(0.0050)	(0.0173)
Full set of other controls	yes	yes	yes	yes
Control for grade	yes	yes	yes	yes
Control for survey year	yes	yes	yes	yes
Control for region	yes	yes	yes	yes
Observations	140,003	140,003	140,003	140,003
R-squared	0.3313	0.3322	0.2103	0.2103

Note: The table reports OLS estimates. The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for grade, survey year and region are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.
Source: our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

results are also comparable when considering the INVALSI tests in math. Finally, the coefficients are comparable to those shown in Table 4.

However, classes located in regions with historical presence of *Mafia* organizations (*HM_REGIONS)* do not seem to gain higher educational outcomes than those achieved by classes located in regions not traditionally related to *Mafia*. Among others, this result may be due to the high heterogeneity in terms of historical presence of *Mafia* organizations within each Southern region.

Table 6 provides the results of the subsample of Southern regions including classes located in Campania, Calabria, and Sicily only (columns 1 and 2) and also classes located in Apulia (columns 3 and 4). Finally, columns 5 and 6 report the estimates for all classes located in the Southern regions. Our main indicator of the presence of *Mafia*-type organizations at the local level continues to be the composite index IPM. Notwithstanding, as a motivation for future research, we investigate here the infiltration of organized crime into public institutions, although it has already been taken into consideration by one of the pillars of the IPM index. Here, we specifically take this into account by replacing the former IPM index in Equation (2) with the IIM index and by estimating the following specification:

$$y_{i,g,k,j,t} = \alpha + \beta_1 CRIME_j + \beta_2 SCHOOL_{i,j,t} + \beta_3 CLASS_{i,g,k,j,t} + \beta_4 FIXED_{EF\,i,g,k,j,t} + \varepsilon_{i,g,k,j,t} \tag{3}$$

where CRIME represents the IPM or IIM indices, respectively, and the other variables are those illustrated above.

In Table 6, for each subsample, the estimates (either with IPM or IIM) provide further support to the role of organised crime in affecting educational performance at class level (*i.e.,* all coefficients are negative and highly significant at the 1% level). Looking at each of the two measures of organised crime, the estimated coefficient of the IPM index shows larger variation across specifications. In fact, one standard deviation increase in the IPM index is associated with a reduction in educational outcomes, ranging from 0.0435 to 0.0994, depending on the subsample. Conversely, the estimated coefficient of the effect of institutional penetration of organised crime on the educational outcome (i.e., the IIM index) is remarkably stable across specifications. One standard deviation increase in the IIM index is associated with a reduction in educational achievements ranging from 0.0181 to 0.0195. Therefore, the former index captures different and more heterogeneous aspects of organised crime compared to the latter.

6.2. Endogeneity issues

We are aware that some endogeneity concerns may arise in previous estimates and that measurement errors, as well as the presence of possible omitted factors, could be another potential source of bias, implying that OLS estimates cannot be interpreted as causal. To control for such issues, we use an instrumental variable (IV) strategy, employing measures related to the historical diffusion of *Mafia* in Southern Italian provinces. Specifically, we consider, as instruments, the spread of *Mafia* organizations at the end of 19th century (MAFIA_HIST) at the provincial level provided by [32] and the land productivity (LANDPROD) measured by the total value of land tax per square kilometres at

Table 6
Subsample of classes in traditionally *Mafia*-controlled regions (dependent variable: standardised Italian language score).

Variables	Traditionally Mafia-controlled regions		Traditionally Mafia-controlled regions plus Apulia		All southern regions	
	(1)	(2)	(3)	(4)	(5)	(6)
IPM	−0.3423***		−0.3350***		−0.1499***	
	(0.0537)		(0.0487)		(0.0302)	
IIM		−0.0907***		−0.0887***		−0.0911***
		(0.0203)		(0.0201)		(0.0203)
Full set of other controls	yes	yes	yes	yes	yes	yes
Control for grade	yes	yes	yes	yes	yes	yes
Control for survey year	yes	yes	yes	yes	yes	yes
Control for region	yes	yes	yes	yes	yes	yes
Observations	33,286	33,286	44,130	44,130	52,510	52,510
R-squared	0.4032	0.4107	0.4009	0.4057	0.3886	0.3901

Note: The table reports OLS estimates in traditionally Mafia-controlled regions (Campania, Calabria, and Sicily in columns (1) and (2); adding Apulia in columns (3) and (4)); all Southern regions in columns (5) and (6) (dependent variable: standardised Italian language score). The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for grade, survey year and region are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.
Source: our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

Table 7
Pairwise correlation between organised crime indices and historical instruments.

		(1)	(2)	(3)	(4)
(1)	IPM	1.0000			
(2)	IIM	0.5650*	1.0000		
(3)	LANDPROD	0.3987*	0.6687*	1.0000	
(4)	MAFIA_HIST	0.4630*	0.7901*	0.6884*	1.0000

Note: *p < 0.01.
Source: our elaboration on data provided by Ministry of Internal Affairs and [15,29,32].

Table 8
IV estimates – All Southern regions (instrumented: IPM and IIM; dependent variable: standardised Italian language score).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
IPM	−0.7206***	−0.6573***	−0.6824***			
	(0.0880)	(0.0788)	(0.0746)			
IIM				−0.3307***	−0.2801***	−0.2991***
				(0.0407)	(0.0398)	(0.0391)
Instruments						
LANDPROD[a]	−0.0001***		−0.0000***	−0.0002***		−0.0000***
	(0.0000)		(0.0000)	(0.0000)		(0.0000)
MAFIA_HIST[a]		−0.0396***	−0.0271***		−0.1094***	−0.0982***
		(0.0007)	(0.0011)		(0.0014)	(0.0022)
Endogeneity test[b]	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
F-statistics[c]	14.04	15.88	11.27	15.07	14.87	12.61
Overidentification test[d]			0.3832			0.1804
Full set of other controls	yes	yes	yes	yes	yes	yes
Control for grade	yes	yes	yes	yes	yes	yes
Control for survey year	yes	yes	yes	yes	yes	yes
Control for region	yes	yes	yes	yes	yes	yes
Observations	52,510	52,510	52,510	52,510	52,510	52,510

Note: The Table reports IV estimates. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for GRADE, SURVEY_YEAR and REGION are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.
[a] First-stage coefficients of instruments.
[b] Reports the p-value of the endogeneity test.
[c] F-statistic of the Kleibergen-Paap rk Wald test for weak identification.
[d] The overidentification test reports the p-value of the Hansen's J statistic of overidentifying restrictions.
Source. our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

Table 9
Confidence bounds relaxing the perfect exogeneity assumption of the instrument: IV estimates – all Southern regions (instrumented: IPM and IIM; dependent variable: standardised Italian language score).

Range of plausible values		IPM		IIM	
LANDPROD		*Lower*	*Upper*	*Lower*	*Upper*
[−0.0001, +0.0001]		−0.9073	−0.5338	−0.4307	−0.2511
[−0.0002, +0.0002]		−0.9217	−0.5195	−0.4222	−0.2437
[−0.0005, +0.0005]		−0.9646	−0.4767	−0.4200	−0.2254
MAFIA_HIST		*Lower*	*Upper*	*Lower*	*Upper*
[−0.1, +0.1]		−0.9385	−0.3775	−0.3973	−0.0927
[−0.2, +0.2]		−1.0654	−0.2519	−0.4417	−0.0577
[−0.5, +0.5]		−1.2778	−0.1010	−0.4807	−0.0007
LANDPROD	**MAFIA_HIST**	*Lower*	*Lower*	*Lower*	*Upper*
[−0.0001, +0.0001]	[−0.1, +0.1]	−0.8619	−0.3160	−0.3160	−0.1915
[−0.0002, +0.0002]	[−0.2, +0.2]	−0.9624	−0.3558	−0.3540	−0.1409
[−0.0005, +0.0005]	[−0.5, +0.5]	−1.1072	−0.4117	−0.4103	−0.0873

Note: 95% confidence lower and upper bounds are estimated according to the approach proposed by [66]. All estimates include the entire set of controls as in Table 8.
Source. our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

provincial level [29]. By doing so, we exploit the effect of the historical spread of *Mafia* in Southern Italian provinces as an exogenous source of variation in the current presence of organised crime at the local level. Formally, our first-stage regression is:

$$IPM_j = a + b_1 Z_r + b_2 SCHOOL_{i,j,t} + b_3 CLASS_{i,g,k,j,t} + b_4 FIXED_{EF\,i,g,k,j,t} + e_{i,g,k,j,t} \tag{4}$$

where Z_r is our vector of instruments including a) the spread of *Mafia* organizations at the end of 1800s (MAFIA_HIST); and b) the land productivity (LANDPROD). Finally, $e_{i,g,k,j,t}$ is an error term potentially correlated with $\varepsilon_{i,g,k,j,t}$ in Equation (3).

The intuition behind our first IV (i.e., MAFIA_HIST) is based on the idea that the historical origins of the Mafia have influenced the contemporary measures of organised crime at the local level. In this perspective, we follow [29] that employ some instruments potentially relevant to our framework. In fact, the previous literature suggests that the origin of organised crime in the South of Italy is largely uncorrelated with modern economic factors but rather to historical characteristics or local situations that have allowed the consolidation of this type of criminal organizations. Since the pioneering work by [28] on the historical origins of the *Mafia*, contemporary measures of organised crime have been explained using historical variables to capture the institutional, socioeconomic, and environmental features of the places where organised crime originally emerged (e.g., [1,2,29–31].

The idea behind our second IV (i.e., LANDPROD) is that land values played a key role in the rise of organised crime at the local level. This transmission mechanism is widely established in the literature. Among others, [64] traces the origin of the Sicilian *Mafia* in 19th century back to the demand for protection by southern landlords when law enforcement was not effective. In this perspective, [28] shows that, due to the importance of agriculture, the value of land area played a fundamental role in the rise of organised crime. Along the same line of reasoning, other papers argue that the Sicilian *Mafia* emerged in response to a demand for protection by the more profitable economic sectors in 19th century. [31] document the existence of a systematic causal link from sulphur availability to the emerge of *Mafia* in Sicilian municipalities, whereas [65] discuss the origin of the Sicilian *Mafia* and verify that its territorial expansion is linked to the land availability for the cultivation of citrus fruits.

As a preliminary validation of our IV strategy, Table 7 reports the pairwise correlations between organised crime indices and historical instruments in our dataset. Our instruments are significantly correlated with organised crime indices. As expected, correlation coefficients are always positive and not negligible. This evidence further supports our empirical strategy of using historical values as instruments for the current presence of organised crime at the local level.

Thus, we re-estimate Equation (3) (and the analogous for IIM) by a 2SLS approach, only for standardized Italian language scores.[35] The results reported in Table 8 support our conjectures. Specifically, columns from 1 to 3 report the results of our IV strategy employing the IPM index, whereas columns from 4 to 6 show the same estimates using the IIM index, which looks at the more limited aspect of the infiltration of

[35] Estimates for mathematics are available from the authors upon request.

Mafia-type organizations into local institutions as measured by municipal councils' dismissions. Overall, the 2SLS estimates are qualitatively consistent with the OLS results reported in Table 6, and the magnitude of the coefficients is quite stable across specifications. Nevertheless, the magnitude of our IV estimates is largely higher than the corresponding OLS ones, suggesting that the latter are downward biased. In fact, using the full specification (column 3), we find that a one standard deviation increase in IPM causes a decrease in the standardised class achievement of about two-thirds of its standard deviation. An equivalent increase in IIM (column 6) causes about 0.05 points decrease in the same outcome.

The standard diagnostic tests reported in Table 8 generally support our IV identification strategy. Specifically, for each estimate, the endogeneity tests reject the null hypothesis that the IPM and IIM indices can be treated as exogenous at conventional significance levels. Furthermore, the F-statistics of the Kleibergen-Paap test for weak identification indicate that our instruments LANDPROD and MAFIA_HIST are not weak.

For all estimates, the first-stage coefficients are always negative and highly statistically significant, consistently with the idea that past socioeconomic characteristics and the historical presence of *Mafia* traits shape the current presence of criminal organizations and negatively affect educational outcomes. Similarly, when we include in the model both the instruments LANDPROD and MAFIA_HIST (columns 3 and 6), the first-stage coefficients are still negative and statistically significant.

Finally, the Hansen's J statistic does not reject our overidentifying restrictions, thus supporting the orthogonality condition (i.e., the error term in the second-stage equation is orthogonal to our instruments).

Despite the comforting results of the diagnostic tests on the validity of our historical instruments, we recognize that the requirement of perfect exogeneity is a quite strong assumption and potentially unlikely to hold up closely. Furthermore, in comparison with the corresponding OLS results in Table 6, the magnitude of the coefficients in Table 8 is even four times larger in some IV specifications, suggesting the possibility that the exclusion restriction assumption has not been met flawlessly.

To address the further concern about the validity of the historical instruments, we check the robustness of our estimates in the event that the instrumental variables do not perfectly meet the exclusion restriction. Therefore, we follow the approach proposed by [66] to construct a confidence interval of the coefficient of interest, employing an instrument that is only plausibly exogenous. More precisely, we relax the strict exclusion restriction assumption of no direct effect of the instrument on the outcome, considering a bound that consists of the union of all confidence intervals in the assumed range of reasonable values. Thus, examining the different bounds, we can estimate the true effect of the organised crime on educational outcomes while deviating from the assumption of perfect exogeneity.

In Table 9, we report the lower and upper 95% confidence intervals of the coefficients of interest for non-zero values of the direct effect of the instrument on the outcome in different plausible ranges (that should be equal to zero to perfectly met the exclusion restriction). Remarkably, regardless of the magnitude of the (non-zero) plausibly endogenous relationship between the instruments and the outcome, the confidence bound of the estimated relationship of interest is quite consistent. This confirms that the impact of organised crime is negative and significant, even when we consider that the adopted instruments are only plausibly exogenous.

7. Concluding remarks

Based on the commonly accepted fact that organised crime harms society in several ways, we have focused our attention on its effects on education because of its long-term relevant contribution to economic growth. Our work adds on to the existing literature in different ways. First, we investigate the relationship between the infiltration of organised crime into the Italian institutions (used as a proxy for parental values transmitted to children, including the lower returns expected from investment in education) and the INVALSI achievements of primary school students in Italian language. After controlling for test manipulation as suggested by [26], we find that the higher the estimated levels of organised crime, the lower the percentage of adjusted correct answers in the Italian language obtained by the classes of the province under analysis.

We show that values transmitted by the family play a role on students' educational achievements. Where these values reflect *Mafia* culture and its priorities, students are expected to perform worse at school. However, we acknowledge that returns from investment in education may not be as relevant if the local level of public safety is not high enough. Thus, the incentives to study might decrease and achieve a low output, showing that the benefits of schooling can only be seized if they are complemented with enough public safety [22].

Second, we develop a new measure of the presence of organised crime at provincial level by constructing a novel index of *Mafia* institutional infiltration (i.e., the IIM index), computed by the ratio between the population of municipalities whose councils have been dismissed because of organised crime infiltration from 1991 to 2011 and the total population of the province.

Finally, we provide a rational explanation for the existing geographical 'learning divide' between the North and South of Italy. This explanation serves as an alternative to those suggesting as main determinant low levels of either socio-cultural values (e.g., [67]: low "civic trust"; [68]: "trust and respect for others, and confidence in individual self-determination") or IQ in Southern regions of Italy [69,70]. Our results show that poor performances in the Southern provinces of Italy are due to the high presence of organised crime that lowers the expected returns to investment in education. Consequently, families pay less attention to the educational outcomes of their sons who, in turn, put less effort in studying.

From a policy perspective, the results arising from this paper outline few directions for an educational policy agenda. Specifically, to achieve better students' performance in those geographical areas where INVALSI scores are lower, policy makers should pursue a twofold approach by: 1) increasing the perceived returns to investment in education (e.g., by reducing the direct and indirect educational costs; by providing fiscal deductions for school expenditures, by giving subsidies to targeted families, etc.); 2) contrasting the infiltration of organised crime into the institutions and fighting the *Mafia* culture through positive examples and encouraging community engagement.

However, it is important to recognize that no single approach can solve the complex problem of low student achievement in some areas of Southern Italy in particular. A comprehensive strategy that combines support for education with efforts to counter negative societal influences is probably needed to achieve long-lasting changes. Policy makers should also be open to evaluating and adapting their strategies based on evidence and feedback from local communities, ensuring that the initiatives implemented are effective and beneficial to the communities concerned.

Author statement

Marina Cavalieri: Conceptualization, Data curation, Writing-Original draft preparation, Writing- Reviewing and Editing, **Massimo Finocchiaro Castro:** Conceptualization, Formal analysis, Writing-Original draft preparation, Writing- Reviewing and Editing.

Calogero Guccio: Conceptualization, Formal analysis, Data curation, Methodology, Writing-Original draft preparation, Writing-Reviewing and Editing.

Data availability

The authors do not have permission to share data.

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APPENDIX A.1. A snapshot of the Italian education system

In Italy education is a Constitutional right/duty (art. 33 and 34), publicly provided free of charge and compulsory for ten years between the ages of 6 and 16. More specifically, compulsory education covers eight years of the first cycle of education (i.e., five years of primary school and three years of lower secondary school), and the first two years of the second cycle. After completion of the first cycle of education, students can undertake the final two years of compulsory education (from 14 to 16 years of age) at an upper secondary school (*lyceum*, technical or vocational institutes), which lasts either five or four or three years. Alternatively, 15-year-olds can also spend the last year of compulsory education by attending an apprenticeship, organised by the Regions upon specific arrangements with the Ministry of Labour and the Ministry of Education, University and Research (MIUR).

Compulsory education can be undertaken at either public schools (free of charge), private but publicly subsidised schools (*Scuole paritarie*), or, subject to certain conditions, at other private schools or even through home education. Parents are entitled to choose any school they want (even within the public sector) and, except for the rare case of oversubscription, they usually get it. Notwithstanding, families generally apply to the nearest school to their home, in the province of residence. At the end of upper secondary education, students sit a state examination. Only if they pass, they are allowed to access to tertiary education (university, high level arts and music education and higher technical institutes).

Following the 2001 Constitutional reform (Constitutional Act n.3/2001), legislative competencies on education issues and responsibilities for the organisation and administration of the education system are shared between the central and the regional level. At the central level, the MIUR is responsible for the organisation/programming/management of the overall school system (e.g., minimum national curriculum and quality standards) and its evaluation, the adherence to the European requirements, the determination and assignment of financial resources, and the recruitment of school staff. The MIUR operates at a decentralised level through the Regional School Offices (*Ufffici Scolastici Regionali*, USR) and their provincial branches (*Uffici Scolastici Provinciali*, USP). The USR monitor compliance with the national education provisions and standards, as well as with the minimum performance requirements. At local level, the USP have no autonomy; they support schools with their administrative tasks and the planning of their own educational offers. Furthermore, once the USR have determined the total number of classes in the region, the USP decide their allocation between schools. Municipalities are mainly in charge of providing school buildings, equipment and facilities, as well as transport service; their assigned specific functions and responsibilities change according to the different levels of education.

Since 2000, schools at primary and secondary level have been granted legal status and autonomy in the fields of administration, education, teaching, and research, though within the general framework laid down by the Ministry of Education to ensure uniformity throughout the Italian territory. Schools can be organised either as single level institutes or as “comprehensive” institutes that include multiple grades (usually, primary, and lower secondary schools). According to the type of organisational structure and to the number of classes, Italian schools differ greatly in size.

All schools are run by a school manager (*Dirigente scolastico*), who is the legal representative of the institution and is responsible for its overall organisation, the management of human, technological and financial resources and the quality of the service provided. Teachers are mainly civil servants, recruited by competitive examinations and with virtually no risk of dismissal. They are paid a fixed salary, which remains one of the lowest among the OECD countries (OECD, 2022). To incentivise teacher performance, the so-called “*Buona scuola*” reform (Law 107/2015) has introduced a merit-based component in the teachers’ salary, in the form of a one-off bonus. This is assigned yearly by an internal school committee to the best performing teachers, based on national guidelines for teachers’ evaluation. However, its limited entity is likely to have only a negligible impact on teachers’ motivation, which is found to be a relevant factor affecting pupils’ achievements in Italy (Barbieri et al., 2017).

To boost competition in the public education sector (both among schools and among teachers), thelaw 107/2015 has empowered the school principals to choose teachers to hire from territorial registers formed by networks of schools, considering teachers’ applications. Once appointed, teachers are reconfirmed every three years, in accordance with the Educational Syllabus (*Piano dell’Offerta Formativa*) of the school.

In the Italian compulsory education system, the development of a national approach for assessing student outcomes can be traced back to the reform that granted school autonomy (Legislative Decree No. 258/1999), and at the same time, to ensure the preservation of homogeneous standards at national level, led to the creation of the National Institute for the Evaluation of the Education and Training System (INVALSI). This led to the creation of a system of national tests that have been refined over time. In the period 2001–2003, three pilot surveys on learning outcomes in schools were completed but only among a limited sample and on a voluntary basis. In 2004 (Legislative Decree 286/2004), the institute was reorganised, formally assigning it the task of managing the systematic and recurrent evaluation of the learning outcomes in the Italian education system. During the same year, INVALSI carried out the first compulsory survey of primary schools. This was, however, strongly criticised because of the lack of a robust research protocol that was likely to generate not reliable empirical findings.

It was only in 2007 with the *Quaderno Bianco sulla Scuola*, a strategic document set by the government Prodi, that the need for a standardised national test was defined to counter “the lack of the culture of evaluation in Italy”, to avoid the risk of a highly fragmented education system (due to greater school autonomy), to improve schools’ capacity to raise the quality of educational outputs and to meet learning outcome targets at national level. Afterwards, the test contents have been redefined based on experts’ opinion and following an intense public debate.

Therefore, in 2007 INVALSI piloted standardised tests in a small sample of voluntary schools in the second and fifth grade, to assess students’ abilities in Italian language and mathematics. The year after, these tests become compulsory for all schools at given grades (second, fifth, sixth, eight and tenth grade).[36] Students are thus requested to compile a hand-written test (the same for everyone), including both multiple choices and open-ended questions. These reflect Italian reading comprehension and grammar competencies as well as knowledge in mathematics, which they should have learned in their school career.[37] The questionnaire is also designed to collect several additional information about students themselves, their family, their parents' educational level and their socio-economic situation, which is then employed to construct a concise index of individual economic, social, and cultural status (ESCS index).

The test is usually administered in the spring period by teachers at schools (other than those of the class and of the subject tested). These are also asked to interpret and faithfully report students' original answers on pre-defined machine-readable score forms, which have then to be sent back to the INVALSI. Along with the risk of cheating during the test compilation, the transcription process by teachers leaves space to ex-post score manipulation phenomena. To control for these moral hazard problems, a representative random sample of schools is selected every year at national level where tests are monitored by external evaluators.

A.2 Descriptive statistics for the whole Italian sample

Table A.2.1
Summary statistics.

Variables	Meaning	Mean	St. Dev.
Outcomes			
ANSWERS_ITAL_PCT [c]	Class percentage of corrected answers in Italian language	72.0772	10.1722
ANSWERS_ITAL_STD [c]	Standardised class percentage of corrected answers in Italian language	0.0100	0.5226
ANSWERS_MATH_PCT [c]	Class percentage of corrected answers in Mathematics	64.0421	13.0273
ANSWERS_MATH_STD [c]	Standardised class percentage of corrected answers in Mathematics	0.0067	0.6370
Controls for geographical area			
NORTH [d]	Dummy for the class in the North of the country	0.4424	0.4967
CENTRE [d]	Dummy for the class in the Centre of the country	0.1826	0.3863
SOUTH [d]	Dummy for the class in the South of the country	0.3751	0.4841
Controls for organised crime at provincial level			
IPM [a]	Index of infiltration of *Mafia*-type organizations	0.6273	0.2903
IIM	Index of *mafia* institutional infiltration	0.0934	0.2909
RT [a]	Composite index of territorial risk of organised crime infiltration	0.4097	0.2555
IR [a]	Index of wealth deprivation	0.5132	0.2694
IS [a]	Index of the diffusion of shadow economy	0.3895	0.2084
IT [a]	Index of lack of market openness and technological adoption	0.4629	0.2400
HM_REGIONS [d]	Dummy for regions with historical presence of *Mafia*	0.0934	0.2909
Instruments			
LANDPROD [b]	Land productivity at the end of 19th century	752.8110	917.2359
MAFIA_HIST [b]	Diffusion of *Mafia* organizations at the end of 19th century	1.4521	1.5955
Other controls at class level			
STUDENTS [c]	Grade enrolment at school	53.2908	30.5651
CLSIZE [c]	Class size	19.8848	3.5765
CHEAT_ITAL [c]	Dummy for class with compromised scores ("suspicious" class)	0.0553	0.2286
MONITORED [c]	Class externally monitored	0.0688	0.2531
FEMALE [c]	Proportion of female students	0.4820	0.1205
M_FEMALE [c]	Proportion of students with missing gender	0.0208	0.1085
IMMIGRANTS_BROAD [c]	Proportion of immigrant students	0.0981	0.1198
M_ORIGIN [c]	Proportion of students with missing origin	0.0296	0.1544
DAD_LOWEDU [c]	Proportion of students whose father is High School dropout	0.4273	0.2561
DAD_MIDEDU [c]	Proportion of students whose father is High School graduate	0.2546	0.1678
DAD_HIGHEDU [c]	Proportion of students whose father is College graduate	0.0994	0.1168
M_DAD_EDU [c]	Proportion of students with missing father education	0.2187	0.3361
MOM_UNEMP [c]	Proportion of students whose mother is unemployed	0.0366	0.0552
MOM_HOUSEW [c]	Proportion of students whose mother is a housewife	0.3206	0.2348
MOM_EMPLOYED [c]	Proportion of students whose mother is employed	0.4503	0.2658
M_MOM_OCC [c]	Proportion of students with missing mother occupation	0.1925	0.3239
M_MOM_EDU [c]	Proportion of students with missing mother education	0.2051	0.3399

Note: Stratification controls also for survey year, grade, and region.
[a] Our computation on data provided by [15].
[b] Our computation on data provided by [29,32].
[c] Our computation on data provided by [26].
[d] Our computation.

[36] More specifically, test taken in the sixth grade has been suppressed since the 2013/14 school year. For a detailed review of the Italian education system, see Appendix A.1.
[37] Since 2018 a new test to assess students' ability in English language has been introduced. Furthermore, all tests for the eight and tenth grades are now computer-based.

A.3 Robustness checks on the whole Italian sample

In this Section we provide some robustness checks on the whole Italian sample. First, the consistency of our results reduces concerns for measurement errors. However, after having controlled for several determinants of educational outcomes and for regional fixed effects, the choice of a simple linear regression with an organised crime index as dependent variable may be subjected to picking up spurious correlations.

Therefore, in the following we provide several robustness assessments. First, we checked whether the simultaneous inclusion of geographic and regional fixed effects in models (1) and (2) could lead to latent multicollinearity problems that even if not identified by the software could result in meaningless and misleading estimates. Tables A.3.1 and A.3.2 show estimates for the (standardized) scores in Italian language like those in Tables 4 and 5 but without regional FE. As can be noted, the results of the estimates in Tables A.3.1 and A.3.2 are qualitatively similar to those previously obtained for the (standardized) scores in Italian language.

Table A.3.1
OLS results on the full sample without regional FE (dependent variable: standardized INVALSI scores).

Variables	Dependent variable		
	Standardised Italian language scores		
	(1)	(2)	(3)
NORTH	0.0797***		0.0711***
	(0.0055)		(0.0055)
CENTRE	0.0658***		0.0501***
	(0.0050)		(0.0052)
IPM		−0.0822***	−0.0640***
		(0.0063)	(0.0064)
Full set of other controls	no	yes	
Control for grade	yes	yes	yes
Control for survey year	yes	yes	yes
Control for region	no	no	no
Observations	140,003	140,003	140,003
R-squared	0.3269	0.3277	0.3285

Source: our elaboration on data provided by Ministry of Internal Affairs and [15,26], by pooling second and fifth grade students for the school years 2009–2011.
Note: The table reports OLS estimates. The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for GRADE and SURVEY_YEAR are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.3.2
OLS results on the full sample without regional FE – adding controls for regions with an historical presence of organised crime (dependent variable: standardised INVALSI score).

Variables	Dependent variable	
	Standardised Italian language score	
IPM		−0.0880***
		(0.00631)
HM_REGIONS	−0.0156**	−0.0350***
	(0.00676)	(0.00687)
Full set of other controls	yes	yes
Control for grade	yes	yes
Control for survey year	yes	yes
Control for region	no	no
Observations	140,003	140,003
R-squared	0.3313	0.3322

Note: The table reports OLS estimates. The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for GRADE and SURVEY_YEAR are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.
Source: our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

Second, to check for measurement errors of our results with respect to different and wider measures of organised crime and to control for environmental factors at provincial level that potentially affect the expected returns of the investment in human capital and, thus, the educational outcomes, we apply the composite index of territorial risk of organised crime infiltration at provincial level (*Indice di Rischio Territoriale,* RT) developed b [15] and its four pillars (one of which is the IPM index).[38]

Although we already consider regional fixed effects, adding these variables enables us to further control for environmental factors at the provincial level that could potentially affect the expected returns of the investment in human capital and, thus, our educational outcomes.

Looking at the first two columns of Table A.3.3, the coefficients of the RT index are never statistically significant, neither when the index is employed alone (column 1), nor when is used jointly with the macro-area variables (column 2). However, the macro-area variables continue to be highly significant (at the 1% level) and with the expected signs. In the last two columns of Table A.3.3 the effects of the four pillars are considered, without (column 3) and along with the macro-area variables (column 4). Even so, the coefficients of the four pillars are always significant. Furthermore, the IPM index continues to be significant, with a corrected sign and a beta coefficient slightly lower than that estimated in Table 4. Thus, this further check again confirms that, at the full sample level, there is a robust and significant association between organized crime and school results.

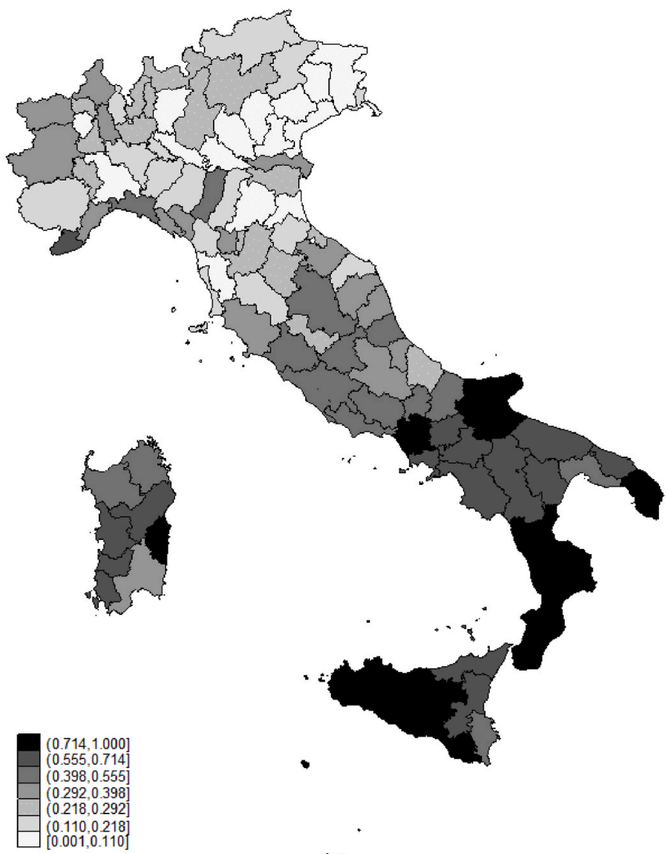

Fig. A.3.1. RT synthetic index at provincial level.
Note: Map displays the composite index of territorial risk of organised crime infiltration at provincial level (*Indice di Rischio Territoriale*, RT) developed by [15].
Source: our elaboration on data provided by [15].

[38] The RT index is computed by aggregating the IPM and three other (normalised) indexes (pillars), using the generalized mean method. The first pillar of the RT index is a measure of wealth deprivation (*Indice di Ricchezza*, IR) constructed by considering per capita GDP, the number of purchased expensive cars (over 2000 cc.) and the average declared income used to compute the Regional and Municipal surtax. The second pillar (*Indice di Economia Sommersa*, IS) captures the diffusion of the shadow economy and it is computed using the following simple indices: levels of tax evasion, tax gap, and number of suspicious transactions reports received by the Bank of Italy. The last pillar (*Indice di Struttura del Mercato nel Territorio*, IT) is a measure of the lack of market openness and of the technological adoption at provincial level. It is obtained by considering R&D expenditure, the endowment of infrastructure at the provincial level and the ratio between the sum of imports and exports and the added value at the provincial level. All the indexes are then normalised to a 0–1 scale, according to a min-max criterion where 1 is equal to the highest value in the 107 provinces. The distributions of the RT and its pillars' values are provided in the following Fig. A.3.1 and A.3.2.

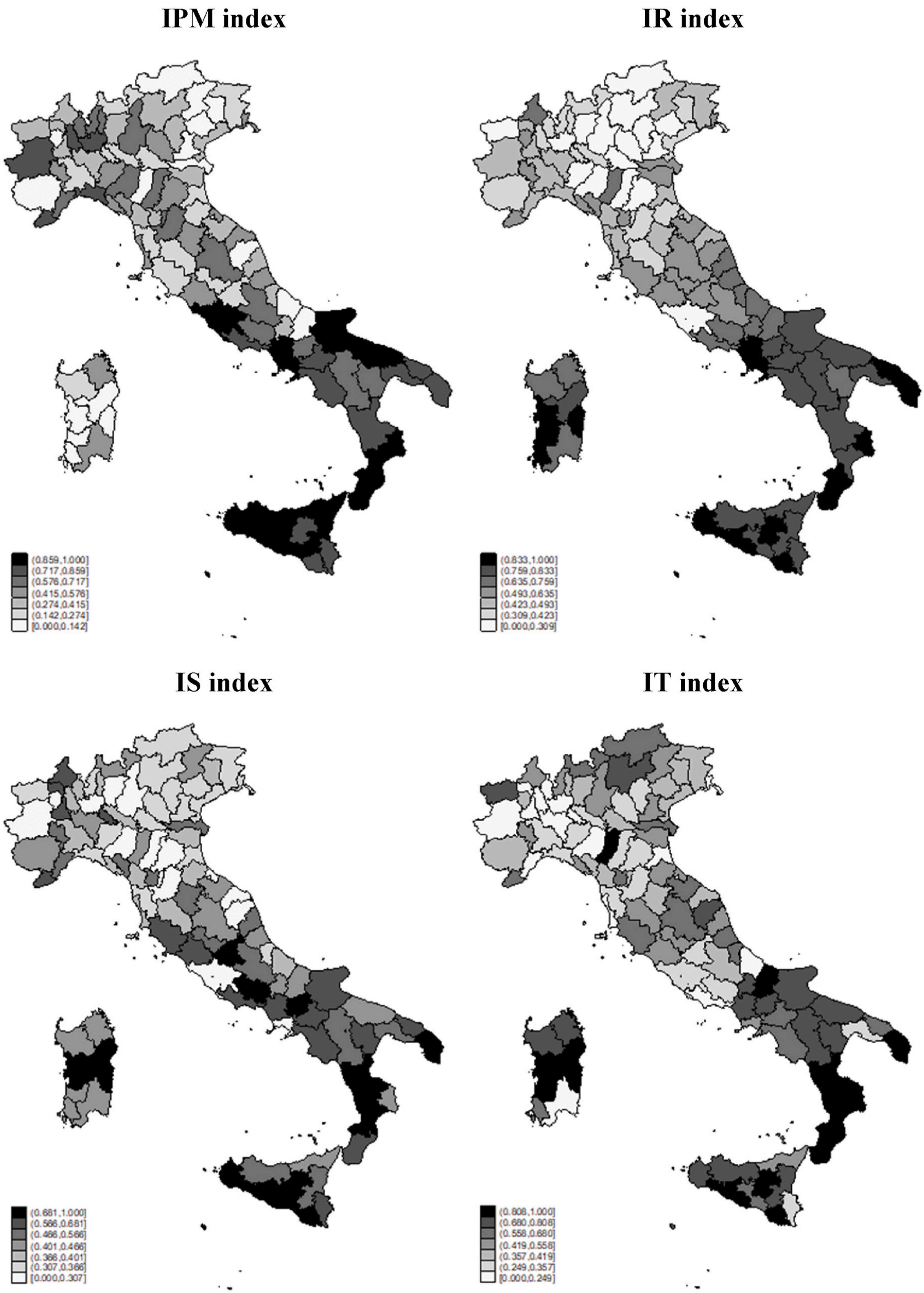

Fig. A.3.2. Pillars of the RT synthetic index at provincial level.
Note: Maps display the four pillars of the RT composite index at provincial level. The first pillar is the IPM index of *Mafia*-type organised crime (*Indice di Presenza Mafiosa*) already reported in Fig. 1. The second pillar is a measure of wealth deprivation (IR, *Indice di Ricchezza*) built considering per capita GDP, number of expensive cars (over 2000 cc.) purchased, and average declared income used to compute Regional and Municipal surtax. The third pillar (IS, *Indice di Economia Sommersa*) captures the diffusion of shadow economy and is computed using the following simple indexes: levels of tax evasion, tax gap, and the number of notifications of suspicious transactions recorded by Bank of Italy. The last pillar (IT, *Indice di Struttura del Mercato nel Territorio*) is a measure of lack of market openness

and technological adoption at provincial level. It has been obtained considering the expenditure in R&D, the endowment of infrastructure at provincial level and the ratio between the sum of imports and exports and the added value at provincial level.
Source: our elaboration on data provided by [15].

Table A.3.3
Robustness check for OLS estimates using the RT index (columns (1) to (2)) and its pillars (columns (3) and (4)) - full sample (dependent variable: standardised Italian language score).

Variables	(1)	(2)	(3)	(4)
NORTH		0.1072***		0.0693***
		(0.0157)		(0.0164)
CENTRE		0.0657***		0.0112
		(0.0128)		(0.0139)
RT	−0.0265	−0.0265		
	(0.0188)	(0.0188)		
IPM			−0.0290***	−0.0290***
			(0.0111)	(0.0111)
IR			−0.2270***	−0.2270***
			(0.0231)	(0.0231)
IS			0.2109***	0.2109***
			(0.0187)	(0.0187)
IT			0.0785***	0.0785***
			(0.0137)	(0.0137)
Full set of other controls	yes	yes	yes	yes
Control for grade	yes	yes	yes	yes
Control for survey year	yes	yes	yes	yes
Control for region	yes	yes	yes	yes
Observations	140,003	140,003	140,003	140,003
R-squared	0.3313	0.3313	0.3346	0.3346

Note: The table reports OLS estimates. The unit of observation is an individual. The models in the Table also control for a full set of variables at SCHOOL and CLASS level. Fixed effects for GRADE, SURVEY_YEAR and REGION are also included. Robust standard errors, clustered on school and grade, are shown in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: our elaboration on data provided by Ministry of Interior and [15,26], by pooling second and fifth grade students for the school years 2009–2011.

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