Eroding Civic Capital: How Persistent Organised Crime Diminishes Tax Compliance *

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Abstract

What is the long-term effect of organised crime presence on civic capital? By leveraging novel tax compliance and organised crime data, this study investigates this question within the Italian landscape from the 1950s to the 2000s. We exploit the forced resettlement law that compelled organised crime members living in the South of Italy to resettle in the Centre-North area of the country. Employing a difference-in-differences estimation strategy, estimates reveal that sustained exposure to mafia presence reduces TV tax compliance. Exploring possible mechanisms, we find that municipalities exposed to the forced resettlement law show more firms in strategic sectors for organised crime infiltration, and more episodes of extortion and labour racketeering.

Keywords: Organised Crime, Civic Capital, Forced Resettlement, Tax Compliance.

JEL: A13, K42, N34, H26.

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1 Introduction

Organised crime has increasingly penetrated various institutional spheres and has harmful effects on local communities.[1] While economics literature has extensively explored criminal organisations' economic and political ramifications (among others Pinotti, 2015; De Feo and De Luca, 2017; Mirenda et al., 2022; Arellano-Bover et al., 2024), there remains a gap in understanding of how its presence erodes civic capital and influences individuals' inclination to comply with the law, key aspects of social trust, and active citizenship (North, 1990).[2] Neglecting to explore this is to overlook the broader societal implications of organised crime.

This paper investigates the long-term impact of criminal organisations on the accumulation of civic capital, focusing on general compliance behaviour proxied by tax compliance. Tax compliance represents a measure of civic culture, capturing trust in state institutions and pro-social attitudes while also being a crucial determinant of fiscal revenues, which are a key indicator of state capacity (Luttmer and Singhal, 2014).

This paper focuses on Italy, as its long-standing history of organised criminal activity and its relevance to the study of civic and social capital (Putnam et al., 1992) make it an ideal case study. In this context, we operationalised civic awareness through the TV license fee compliance rate, using newly digitised data stretching from the 1950s to the 2000s at the municipality-decade level. This serves as a direct and observable measure of the degree of citizens' interaction with the state (Bracco et al., 2015; Bracco et al., 2021). Our focus is on the Central and Northern regions, which are recognised as the most economically advanced areas of Italy and have recently been targeted by expanding criminal organisations (Mirenda et al., 2022).

Assessing the causal impact of organised crime presents several challenges due to the non-random nature of its presence. Organised crime infiltrates areas where it can expand its interests, making it difficult to establish causal links. To address this challenge, we exploit a law known as *"soggiorno obbligato"* or *"confino"*, which mandated the forced resettlement of members of criminal organisations from Southern to Central-Northern Italy between the 1960s and 1970s. This allows us to pinpoint a precise period for the arrival of criminal organisations in the area. The law aimed to disrupt the local connections of members of criminal groups and relocate them away from their home areas, mainly in the Centre-North regions. Decades after its introduction,

[1] Henceforth, "organised crime" and "mafia" are used interchangeably.

[2] Civic capital refers to *"shared beliefs and values that help a group overcome the free rider problem in the pursuit of socially valuable activities"* (Nannicini et al., 2013; Guiso et al., 2011).

Smuraglia (1994) identified the policy as facilitating the expansion of organised crime from the South to the Centre-North. We gather novel data on displaced criminals at the municipality level from the Italian Parliamentary Antimafia Commission (IPAC). We then complement this data with a time-varying measure of organised crime presence, constructed by web-scraping news articles relating to organised crime and published between the 1950s and 2000s from the public online archive of a national Italian newspaper. This approach provides a measure of the comprehensive and long-term presence of organised crime at the municipal level dating back to the 1950s.

Empirically, we employ a standard difference-in-differences (DiD) design that compares TV license fee compliance rates in municipalities which did or did not receive those subject to forced resettlement, before and after their arrival. We find that exposure to the forced resettlement law lowers the TV license fee compliance rate by 1.8 percentage points. This effect implies a direct average loss in state revenue of roughly 47.5€ million in real terms. Event study estimates support the validity of the static ones and support the parallel trends assumption. Further, the coefficients remain negatively stable, suggesting that the main effect is persistent over the long term.

The main results are robust to various robustness checks. These include the employment of time-varying control variables, the exclusion of municipalities with pre-law news relating to organised crime, and combining TV and radio license fee compliance rates for the earliest period in our sample. Additionally, the estimates remain consistent when alternative estimation methods, such as a two-stage least squares (2SLS) and Poisson pseudo-likelihood, are applied. To address potential biases in the application of the forced resettlement law, we exploit a propensity score matching (PSM) (Rosenbaum and Rubin, 1985) technique. Lastly, we explore potential heterogeneity in our results by examining the role of population size, finding that the results remain consistent across different population levels.

Exploring some of the mechanisms through which organised crime may affect tax compliance, we first show its impact on the local economy. We find that municipalities where organised crime is present register more firms in the mining and construction sectors, which are known to be strategic for criminal infiltration. Further, exposure to organised crime yields a higher incidence of extortion and labour racketeering episodes. This evidence suggests a distortion of resources and the use of criminal practices. Combined, these factors can reduce tax compliance by distorting economic incentives, undermining legitimate businesses, and fostering informal markets. They also weaken state institutions, erode trust in the rule of law and discourage civic engagement. In relation to this, we openly discuss how organised crime can alter civic values, diminishing the sense of shared responsibility and further decreasing willingness to comply with tax regulations. However, limited data availability prevents us from empirically testing this mechanism. We then explore how the effects of organised crime on tax compliance may vary depending on specific population characteristics. These impacts are more pronounced in municipalities with younger populations, less homeownership, and higher newspaper readership.[3] Lastly, we acknowledge the potential role of migration, but rule out its interplay with the forced resettlement policy as a primary factor within our setting.

This paper contributes to several strands of the literature. First, it contributes to the literature on the causes underlying the expansion of organised crime (Varese, 2011; Buonanno and Pazzona, 2014; Dipoppa, 2023) and its consequences. In terms of consequences, most of the literature focuses on effects related to political (such as Daniele and Geys, 2015; De Feo and De Luca, 2017; Alesina et al., 2019) and economic dimensions (including Calamunci and Drago, 2020; Di Cataldo and Mastrorocco, 2021; Le Moglie and Sorrenti, 2022; Piemontese, 2023; Arellano-Bover et al., 2024). A more limited strand of the literature focuses on human capital accumulation (Coniglio et al., 2010; Caglayan et al., 2021; Cavalieri et al., 2023) showing how organised crime can hinder its development. A few other studies focus on its effect on social capital accumulation. Specifically, Buonanno et al. (2024) highlight the positive impact of an anti-mafia policy—municipality dissolution—on social capital. In contrast, Rolla and Justino (2022), employing unique survey data mostly within a correlational setting, demonstrate the detrimental effects of organised crime on institutional and interpersonal trust. By examining the relationship between organised crime and tax compliance within a plausibly causal framework, this paper establishes a robust connection between organised crime presence and tax evasion and an overall novel perspective on the broader civic consequences of organised crime.

Second, this paper contributes to the existing literature on how exposure to crime and corruption can affect pro-civic behaviour and trust over time (Anderson and Tverdova, 2003; Chang and Chu, 2006; Gächter and Schulz, 2016; Banerjee, 2016; Gulino and Masera, 2023). Further, it intersects with research that studies the determinants of tax compliance (Luttmer and

[3]Communities with younger populations may be less willing to tolerate opportunistic behaviour, leading to the erosion of civic trust and lower tax compliance. Municipalities with lower rates of home ownership may exhibit weaker attachment to the community amongst their residents. Additionally, higher levels of media consumption can amplify awareness of the presence of crime, negatively influencing individuals' attitudes toward tax compliance.

Singhal, 2014; Besley, 2020). We show and discuss how organised crime affects tax compliance through monetary (extrinsic) and non-monetary (intrinsic) channels. This result is particularly significant as our study uniquely focuses on a context with solid institutions, relevant economic conditions, and dynamic civil society, underlining how organised crime can still substantially impact tax compliance despite these favourable factors.

Lastly, our research aligns with the existing body of work on civic capital and its determinants (Guiso et al., 2011; Nannicini et al., 2013; Bracco et al., 2015; Sgroi et al., 2020; Bracco et al., 2021; Buonanno et al., 2023). We contribute to this literature by examining the impact of external factors, such as organised crime, on civic capital formation. Given the overall pivotal role of civic capital in the development of societies, it is vital to unravel new factors that can affect its accumulation. Moreover, we compile a novel municipality-level dataset on the TV license fee compliance rate that proxies civic capital. To the best of our knowledge, this data is unique and can be helpful for any research on civic capital from a long-run perspective.

The rest of the paper is organised as follows. Section 2 describes the historical background of organised crime and explains the resettlement policy in detail. Section 3 describes the multiple data sources gathered for the development of this paper. Sections 4 and 5, respectively, present the empirical strategy and the associated results. Section 6 describes the robustness checks performed. Section 7 provides a discussion of the potential mechanisms, and Section 8 concludes.

2 Historical background: organised crime expansion in the Centre-North of Italy

The presence of criminal organisations in the South of Italy is notable for its historical longevity and territorial roots (Sciarrone, 1998; Gambetta, 1993). At the same time, such a presence has long been denied in the Centre-North area. Only recent evidence shows that criminal organisations' economic and territorial relevance is significant and growing in this area (Transcrime, 2013; Mirenda et al., 2022).

Serious attention began to be paid to the expansion of mafia organisations beyond their traditional territories in the 1990s (Smuraglia, 1994; Sciarrone, 1998), when the parliament appointed a special committee to investigate the territorial ramifications of such expansion, attributing its transplantation to causes both internal and external to criminal dynamics.[4] Among the exter-

[4]Smuraglia (1994), pages 19-22 of the report.

nal causes that arose from exogenous shocks outside criminal networks, the special committee identified two prominent explanations: 1) the change in the demographic fabric of some areas of the Centre-North induced by the combination of an increase in migration from Southern regions since the 1960s and an increase in labour demand resulting from the economic upturn of the Centre-North area, and 2) the use of forced resettlement, which we shall explain in detail.[5,6]

2.1 Institutional details of the forced resettlement law

Forced resettlement was introduced with Law 1423/1956 and applied to civilians *"deemed socially dangerous"*, as a legacy of a Fascist regulation aimed at isolating political opponents of the state. It was later perfected by Law 575/1965, which specifically targeted individuals associated with organised crime.[7] In 1995, the forced resettlement law was repealed.

The law intended to mitigate the risk posed by individuals who were believed to be linked to criminal activities but could not be indicted due to insufficient evidence. The provision mandated the relocation of these individuals for a period ranging from one to five years so that they could be re-educated and integrated into an upstanding context. The aim was to sever ties between the offender and their criminal network, disrupting the mafia's established structures. Additionally, the law allowed them the freedom to decide whether to stay in their new locale upon completion of the relocation period.

Its application implied that, if a public threat or risk could be correlated to an individual, *"the Questore [Police Commissioner, i.e. the head of police in a specific city], or the National Antimafia Prosecutor, or the State Prosecutor, can ask the court to order forced relocation to a town, then decided by the President of the Court, that has appropriate territorial and safety characteristics [...]»*. The judge who headed the tribunal in the province to which the suspected criminal belonged decided the place and length of their stay, while the law required the displaced to 1) not travel too far from the chosen locale without giving notice to the judicial authority, and 2) to report to the public security authority responsible for surveillance.

[5] The committee points out that: *"This type of immigration is not in itself a criminal phenomenon nor a phenomenon to be regarded with suspicion. Otherwise, a real injustice would be committed to the many workers who moved to the Centre-North with their families and lived honestly"*. However, since the migratory movement was consistent, together with honest immigrant workers individuals more inclined to engage in criminal activities arrived in the area, supporting criminal groups in need of safe bases or references.

[6] Smuraglia (1994) wrote: *"The policy of forced resettlement, largely used without careful choices and appropriate guarantees of control, has practically dispersed in many areas in Italy several individuals belonging to the mafia and has implanted them in areas that would have probably been otherwise immune. [...] people gradually moved into the area, brought their families there, and created a favourable environment for their activities. It was a process that polluted the entire national territory"*.

[7] This marked the first use of the term "mafia," introducing the category of mafia suspects.

However, the law was vague and did not specify the required characteristics of the towns to which mafia members were to be relocated.[8] Some details are available in Camera and Senato (1976), which contains the result of an inquiry into the implementation of the policy and specific questions used by the President of the Palermo Court to gather information on the selection process for destination towns.[9] The document highlights how the implementation of the policy generated a flow of mafia members from the South to cities in Central and Northern Italy. Additionally, according to the President of the Palermo Court: *"there are lists compiled by the Ministry of Interior, [...]. The lists underwent revisions over time [...]. The same Ministry establishes how many confinati can go to each municipality. The court then decides to send these people where they can be easily monitored."* Unfortunately, the document does not include the aforementioned list or provide details on its compilation process.

3 Data

3.1 Forced resettlement

We gather municipal-level data on forcibly resettled members of organised crime groups from several sources. The first is composed of the documents comprising the IPAC list of criminals relocated between 1965 and 1975.[10] Unfortunately, the documents do not provide exact relocation dates.[11] We gather the names of the criminals, their origins, and their destinations. Second, we extend the data on forcibly resettled members of organised crime groups that belonged specifically to the 'ndrangheta, with the data coming from various sources and relating to the period from 1974 to 1995.[12] To the best of our knowledge, this is the most comprehensive data on forcibly resettled members of organised crime at the municipal level. Figure 1 shows, in panel (a), the distribution of municipalities receiving forcibly resettled members of organised crime groups in our dataset, while panel (b) shows the share of forcibly resettled members of organised crime's surnames in contemporary populations.[13] Notably, in panel (a), the distribution

[8] In 1982, amendments were made to incorporate specific characteristics of the destination town. Specifically, *"the compulsory stay must be arranged in a municipality with a population of no less than 5 thousand inhabitants and far from large metropolitan areas, such as to ensure effective control of people subjected to the preventive measure and which is the seat of a police office."*.

[9] Camera and Senato (1976), pages 537-538.

[10] "Documentazione Allegata alla Relazione Conclusiva della Commissione Parlamentare d'Inchiesta sul fenomeno della Mafia in Sicilia, Doc. XXIII, n.1, Volume primo" and "Volume quarto, tomo ventiduesimo", pages 5-30. Figure A6 reports an example of the list

[11] Except for the Liguria region.

[12] We are thankful to Lucia Rizzica and Sauro Mocetti for sharing essential data that complements ours.

[13] To compute this share, we exploit data on Italian taxpayers for 2008. The dataset was published online in 2008 by the Italian Ministry of Finance as a complete set of individual tax declarations. It was subsequently

of municipalities receiving resettlers is relatively homogeneous across the Centre-North of Italy. In panel (b), a considerable cluster is evident in the area surrounding Milan, where multiple organised crime units are now present, in line with Transcrime (2013). Lastly, panel (c) shows a positive correlation between the distribution of forced resettlement and the share of resettler surnames today, suggesting a long-lasting presence of criminal organisations.

3.2 Organised crime presence

Measuring the presence of organised crime from a historical perspective is challenging as most municipal-level indicators are only available from the early 1980s onward (Dugato et al., 2020). To address this, following Dipoppa (2023), we web-scrape news containing the words "*mafia*", "*camorra*", and "*'ndrangheta*" from the *La Stampa* newspaper online archive for the 1950 to 2006 period.[14] From the extracted articles, we collect details such as date, page number, location tags and body text. Then, exploiting location tags and body text, we classify whether a municipality is related to a mafia-related news article on a given date.[15] Lastly, for each municipality and decade, we count the number of news articles concerning organised crime, which is formally our indicator. Figure A1 maps the inverse hyperbolic sine (IHS) transformation of mafia-related news articles across Italy's Centre-North by decade. Larger cities, particularly in the North-West, display the highest values, with the number of news articles increasing over time, peaking in the 1990s, and declining in the 2000s—consistent with the introduction of stricter anti-mafia laws in the 1990s following notable killings.

To analyse the content of these articles, we applied a latent Dirichlet allocation (LDA) model. After standard pre-processing (e.g., removing stop-words, punctuation, and symbols), we estimated the model with 20 topics. Figure A2 shows that the identified topics are primarily related to organised crime activities, such as drug trafficking, arrests, money laundering, and homicides.[16] To assess the validity of our indicator, in Table A1 we regress its average IHS transformed value on confiscation dummies (goods and firms associated with organised crime), i.e., official indicators of organised crime presence for the period 1980-2020.[17] We perform

removed following the intervention of the Italian Privacy Authority, which deemed that the online publication of individual earnings did not conform to the law. individual earnings did not conform to the law. We employ this data source merely in aggregate in this paper.

[14] *La Stampa* is a nationally available newspaper outlet founded in 1867 in Turin. Its online public archive covers the period from 1867 to 2006. To our knowledge, it is the only online public archive covering such an extended period. Appendix A.2 reports examples of the extracted news.

[15] If an article we have extracted contains the name of one or more municipalities, we classify that mafia-related news item as related to that set of municipalities.

[16] Appendix B details this methodology.

[17] The data on confiscations comes from the National Agency for the Management of Goods Confiscated from

this task for different periods, overlapping periods with the entire length of our mafia presence indicator and overlapping periods restricting the length of our mafia indicator to be the same as the confiscation dummies. Overall, our mafia-news-based indicator consistently and positively correlates with the various dummies, with consistent levels of statistical significance.

3.3 Civic Capital: TV tax compliance

To proxy the civic capital dimension, we consider individuals' propensity to free-ride as indicated by their payment of the TV license fee. The economics literature supports using this measure to build a reliable proxy for individuals' propensity to free-ride (Bracco et al., 2015; Buonanno et al., 2023) for two main reasons. First, this tax is relatively inexpensive and easy to evade. In Italy, every TV owner must pay a license fee of between 104€ per year in 2007 and 113.50€ per year in 2014. An administrative sanction is weakly enforced on those who do not, and citizens' typical fines per household are low relative to cost (up to 516€, plus the mandatory purchase of a five-year license).[18] Secondly, as in many other European nations throughout the research period, public broadcasting programmes are available regardless of whether TV owners pay the license fee, making its payment a public benefit contribution with little incentive to comply. As a consequence, one's propensity to pay the TV license fee depends on one's willingness to contribute to the greater public good, or on a sense of civic awareness, reflecting the propensity to accomplish one's civic duty by paying taxes.

In Italy, the TV license fee (i.e., the "Canone RAI") was established under Royal Decree-Law 246 of 21 February 1938, which initially regulated radio subscriptions for those who owned at least one device and was later expanded during the 1950s to include television reception. During this period, radio became a vital part of Italian life, with ownership increasing across income levels alongside increased availability.[19] As Italy's economy improved, television was introduced in the mid-1950s. This was initially a luxury reserved for the wealthy due its high cost. However, proactive industry efforts and economic growth quickly made televisions present in a broader set

Organised Crime (ANBSC).

[18]Exceptions apply in the payment of the fee. Those who are not subject to it include 1) those who do not own a TV device; 2) army members and diplomats; 3) retailers or repairers of TVs; 4) elderly people aged above 75 and with an annual income below 8,000€ https://www.agenziaentrate.gov.it.. In 2016, as a result of relatively common evasion of the fee, the Italian government passed new legislation that requires home energy providers to include the TV license fee in their bills.

[19]Radio served as a propaganda tool during the Fascist era. Post-1937, radio prices dropped with the development of cheaper devices, making them more accessible. Bank of Italy data from 1948 highlights a significant rise in demand for durable goods, including radios (https://www.bancaditalia.it). By 1955, RAI reported over five million licenses in use.

of Italian households. This shift influenced the set of goods monitored by the Italian National Institute of Statistics (ISTAT), reflecting radio and TV's integration into Italian homes and changing consumer habits.[20]

We collect data on the TV license fee compliance rate from RAI, gathering information on the TV license fee compliance rate of households within each studied municipality. This measure is constructed by taking the ratio between the number of TV licenses in a municipality and the number of households with at least one device.[21]After receiving yearly data in PDF format, we design a script that is able to convert them at intervals of five years in structured data.[22] Then, we compute decade averages at the municipal level to construct a panel at the decade level for the period from the 1950s to the 2000s. Figure 2 shows the evolution of the TV license fee compliance rate over time by region, showing a homogeneous pattern across regions, while Figure 3 shows the geographical distribution of the average TV license fee compliance rate at the municipality level by decade.

3.4 Other data

To facilitate the study of potential mechanisms, those data are complemented with municipalities' characteristics derived from ISTAT censuses from 1951 to 2011. Each year serves as a proxy for the characteristics of the decade. We include information such as population, indices measuring local socio-demographic structure, altitude, area, and employment by macro-sector, and information about the number of firms by one-digit sector (i.e., mining, construction, etc.). The latter variables allow us to measure local economic activity as the number of firms registered in a municipality, by one-digit sector. We also collect data on local newspaper diffusion at the provincial level from a private agency, ADS (Accertamenti Diffusione Stampa).[23] Then, we collect data on internal migration from the Institute of Research on Population and Social Policies (IRPSS). Specifically, we gather an arrivals-departures matrix at the province-year level for the whole of Italy, from 1955 to 2014, based on census data from ISTAT. We aggregate data at the decade level and focus on internal migration from the South to the Centre-North of Italy. Table 1 shows the descriptive statistics for all the main variables used in the empirical analysis.

[20]Starting from 1953, ISTAT (https://www.istat.it) included radios and TVs in the basket of goods, along with furniture, utensils, and miscellaneous household items, and included the TV license fee itself as a service fee.

[21]The number of households is calculated yearly with methodological changes to distinguish resident families from those who cohabit.

[22]See Appendix B for details.

[23]We collected data on the circulation of the newspapers *La Stampa*, *Corriere della Sera*, *La Repubblica*, and *Il Messaggero* for the year 1980.

4 Empirical Framework

Using a simple OLS regression to investigate the research question is likely to produce biased estimates for at least three main reasons. First, there may be reverse causation, in which case we cannot rule out whether or not high/low levels of civic capital imply the presence of organised crime. Second, even assuming that the direction indicates that organised crime affects civic capital, it is known from the relevant literature that the presence of organised crime is endogenous. Organised crime may settle, and then operate, in municipalities with lower levels of civic capital. Third, there is the possibility that some omitted variables affect both civic capital and mafia presence. To deal with these issues and hence address potential endogeneity in our estimates, we exploit the forced resettlement law as a plausibly exogenous shock to the expansion of organised crime to the Centre-North of Italy, as discussed in Section 2.[24]

4.1 Difference-in-differences

The main empirical strategy we apply is a difference-in-differences (DiD) approach that compares the TV license fee compliance rate in municipalities which did or did not receive forced resettlers, before and after their arrival. The DiD baseline equation of interest is, therefore,

$$TV_{i,t} = \alpha + \beta Confino_{i,t} + \psi \mathbf{X'}_{i,1950} * \tau_t + \gamma_i + \tau_t + \epsilon_{i,t} \tag{1}$$

where $TV_{i,t}$ is the IHS of the TV license fee compliance rate in municipality i at decade t. $Confino_{i,t}$ is a dummy equal to 1 if a municipality i received a forced resettler. It is equal to 0 in the pre-1970 period and equal to 1 from 1970 onward.[25] $\mathbf{X'_{i,1950}} * \tau_t$ is a vector of control variables in the municipality i in the 1950 decade, i.e. baseline, multiplied by decade fixed effects. The variables in the vector are those which show statistical unbalance in Table

[24] The forced resettlement law has been previously used in literature on the economics of crime. For instance, Buonanno and Pazzona (2014) examine the interaction between the regional number of criminals affected by the law and migration to study its effect on criminal activity. Meanwhile, Scognamiglio (2018) uses a DiD design to estimate the law's impact on criminal activity and employment in the construction sector. Similarly, Caglayan et al. (2021) exploit the forced resettlement law as an instrument at the provincial level to investigate the relationship between organised crime and human capital. Lastly, Pinotti and Stanig (2016) also leverage the law as an instrument to explore the relationship between organised crime and criminal activity at the municipality level.

[25] As mentioned in Section 2, none of the official data include the specific dates for forced resettlers' arrival, which would have allowed us to implement a staggered DiD. Instead, they cover the period from 1965 to 1975. As a consequence, we follow the most relevant previous literature on the categorisation of the forced resettlement variable (Scognamiglio, 2018).

A2.[26] γ_i, τ_t are city and decade fixed effects. Additionally, depending on the specification, we augment this set of fixed effects by adding: municipality linear trends to account for the linear evolution over time; region or province dummies interacted with decade fixed effects to control non-parametrically for regional and provincial trends. Errors are robust clustered at the municipality level.

In this context, DiD empirical strategies require the validity of the parallel trend assumption: that is, that both exposed and unexposed municipalities followed parallel trends in the outcome before the implementation of the policy.[27] Hence, we estimate an event study setup that allows us to assess the validity of the parallel trend assumption. Formally, we estimate the following event study specification,

$$TV_{i,t} = \alpha + \sum_{p=-2}^{+4} \beta_p Confino_{i,t+p} + \psi \mathbf{X'_{i,1950}} * \tau_t + \tau_t + \gamma_i + \epsilon_{i,t} \tag{2}$$

where $Confino_{i,p}$ is the variable related to forced resettlement, restructured to be a series of dummy variables, with $p = 0$ in 1970. We inspect up to $p = -2$ decades prior, i.e. 1950 and 1960, and up to $p = +3$ decades after, i.e. from 1980 to 2000. The omitted period is $p = -1$, i.e. 1960. We include the same set of controls $\mathbf{X'_{i,1950}}$ previously used interacted with decade fixed effects, and we still add decade and municipality fixed effects, τ_t and γ_i, respectively. It is important to stress that, given the imbalance of municipal socio-demographic characteristics between exposed and unexposed municipalities, as highlighted in Table A2, the parallel trend assumption should hold conditional on covariates.

4.2 Instrumental Variable

Alternatively, we use an instrumental variable approach and estimate the following 2SLS system of equations,

$$Mafia_{i,t} = \alpha + \beta Confino_{i,t} + \psi \mathbf{X'}_{i,1950} * \tau_t + \gamma_i + \tau_t + \epsilon_{i,t} \tag{3}$$

$$TV_{i,t} = \alpha + \beta \widehat{Mafia}_{i,t} + \psi \mathbf{X'}_{i,1950} * \tau_t + \gamma_i + \tau_t + \epsilon_{i,t} \tag{4}$$

[26]Table A2 evaluates the balance between municipalities which were exposed to the forced resettlement policy and those which were not, along the set of socio-demographic characteristics previously introduced. Quite a few of these show statistically significant differences between the two groups. Namely, those municipalities which received forced resettlers tend to be more populous, in terms of raw population and area numbers and in terms of density, with a higher share of elderly people, lower house ownership rates, more illiteracy, economies that favour industry, commerce and tertiary sectors at the expense of agriculture, and lower altitudes. This suggests that the forcible resettlement was generally into urban rather than rural areas.

[27]We wish to reiterate that the lack of granularity of the forced resettlement data makes the application of a staggered design unfeasible.

where $TV_{i,t}$ is the IHS of the TV license fee compliance rate in municipality i at decade t. $Mafia_{i,t}$ is the IHS of the number of news in the city i at decade t related to the mafia. $Cofnino_{i,t}$ is the instrumental variable, a dummy equal to 1 if a municipality i received a forced resettler. It is equal to 0 in the pre-1970 period and equal to 1 from 1970 onward. We include the same set of controls $\mathbf{X'_{i,1950}}$ previously introduced interacted with decade fixed effects, and we still add decade and municipality fixed effects, τ_t and γ_i, respectively. Lastly, depending on the specification, we include municipality linear trends and region or province dummies interacted with decade fixed effects. Errors are robust clustered at the municipality level.

The reliability of the 2SLS approach relies on assumptions such as monotonicity, validity, strict exogeneity and exclusion restriction. In contrast, the DiD empirical strategy of the reduced form and the first stage rely only on the parallel trend assumption, conditional on covariates. For this reason, the primary empirical strategy of choice is the DiD of the reduced form with the forced resettlement instrument. However, Appendix C is fully dedicated to discussing the credibility of the 2SLS estimation.

5 Results

5.1 DiD estimates

We begin by showing the results of our event-study specification in Figure 4. Each sub-figure employs different set of fixed effects with confidence intervals at the 95% level. Importantly, at $p = 1950$ there is no sign of a statistically significant difference in the TV license fee compliance rate between exposed and unexposed municipalities, supporting the parallel trends assumption. This is reassuring concerning the validity of the forced resettlement law as a plausible exogenous shock to the investigated outcome. Further, the dynamic analysis displays an immediate drop in compliance post-resettlement, with coefficients from the 1970s onward remaining negatively stable. This suggests that the main effect is persistent in the long term, aligning with the hypothesis that organised crime presence erodes the civic capital and tax compliance of the local population.

To better understand this result, we exploit data on news relating to organised crime and analyse it alongside the forced resettlement policy within this dynamic setup. Figure 5 shows the result of this empirical exercise. Again, at $p = 1950$, no statistically significant differences arise between exposed and exposed. However, the post-forced resettlement period exhibits notable trends. Coefficients of mafia-news increase until the 1990s, after which they sharply decline. This aligns with evidence on the effectiveness of stricter laws against organised crime introduced in the 1990s.[28]. These laws were introduced due to an increase in violent incidents in the previous decades. Consequently, members of criminal organisations shifted their strategy to one less news-worthy but not less effective.

Turning to the DiD estimates, Table 2 shows the outcomes associated with the related estimating equations. Columns (1) to (4) vary depending on the fixed effects included in the estimating equations. Specifically, column (1) includes decade and municipality fixed effects, column (2) adds municipality linear trends to account for different municipality-specific trends over decades, column (3) adjusts the outcome by including region times decade fixed effects to account for region-specific shocks, while column (4) does so with province times decade fixed effect to account for province-specific shocks. All columns include the vector of unbalanced controls outlined in Table A2 at baseline interacted with decade dummies. Overall, the results highlight a significant reduction in the TV license fee compliance rate following the forced resettlement of organised crime members. The effect is stable across columns. Specifically, taking as a reference column (4), which is the most conservative, exposure to the forced resettlement policy lowers the TV license fee compliance rate by 1.8 percentage points. This corresponds to a 3.39% decrease, given a mean outcome of 53.045. Note that this is a decadal magnitude; hence, the yearly effect is 0.339%. One should bear in mind that this effect is likely a lower bound, given that, as do most studies which focus on organised crime econometrically (Di Cataldo and Mastrorocco, 2021, for example), we measure it with its observed activities without accounting for the unobserved ones, unavoidably introducing measurement error.

The effect persists across various robustness checks. In one test, instead of controlling for the vector of unbalanced covariates at baseline, we switch to time-varying controls to capture temporal changes in control variables. Despite being more endogenous, this should reduce the risk of mistakenly attributing local trends or external shocks to the main effect. Column (1) of Table A3 shows that these estimates remain negative and statistically significant as compared to the main effect. The magnitude increases by a factor of almost six, validating the initial choice to employ the controls at baseline, interacted with decade fixed effects.

The main coefficients are also not sensitive to the use of the IHS transformation of the dependent variable. Previous literature shows that the IHS transformation, despite having the attrac-

[28]As reported by *Repubblica*: https://www.repubblica.it

tive feature of being well defined for variables with value 0, is sensitive to measurement units (Bellemare and Wichman, 2020; Aihounton and Henningsen, 2021) and prevents researchers from interpreting average treatment effects (ATEs) as a percentage change (Chen and Roth, 2024). Thus, following Chen and Roth (2024), we employ a Poisson pseudo-likelihood estimator without applying any IHS transformation. Column (2) of Table A3 shows that the estimates remain negative, statistically significant and identical to that of Column (4) of Table 2.

Further, we identify and exclude from the analysis the municipalities that saw any news reports relating to organised crime in the pre-period decades, namely 1950 and 1960. This should allow us to identify choices that are likely manipulated. Column (3) of Table A3 shows the re-estimation results of this exercise, and reassuringly the coefficients remain negative, slightly more prominent, and statistically significant. Lastly, we add the radio tax compliance rate to the TV license fee compliance rate.[29] Column (4) of Table A3 shows the estimates with this newly reconstructed dependent variable. Reassuringly, these estimates are consistent with the main estimates.

5.2 2SLS estimates

Table 3 reports OLS and 2SLS second-stage estimates related to Equation 4. Overall, 2SLS estimates depict a negative and stable pattern for the relationship between the TV license fee compliance rate and the number of news reports relating to organised crime, with values ranging between -0.235 and -0.153. Of the four columns, only the estimate in column (4) is not statistically significant. Taking as a reference the coefficient of Panel B column (1), a 10% increase in the amount of news related to organised crime implies a 2.35% decrease in the TV license fee compliance rate over ten years, with a yearly effect of 0.235%. Panel B reports the KP and CD F-statistics for weak identifications of the first stage, with values ranging from 12.970 to 11.460 and from 50.548 to 36.873, respectively. In Appendix C, we provide a comprehensive discussion on the validity of IV assumptions. We outline the conditions under which the forced resettlement policy qualifies as a valid instrument, allowing the IV estimand to be interpreted

[29] The use of the TV license fee as a proxy of civic capital is well established in the relevant literature (see Section 3). However, one potential issue is that it only those who own at least one television are subject to the license fee. Related to this, in the early years of our sample TVs may not have been so widespread, especially among the poorer population. Hence, this measure may be related to households' disposable income: i.e. high household income if the household has a TV, and low household income if not. Two factors mitigate these concerns. First, as previously mentioned, RAI calculates the number of families by considering those who own at least one device. Second, in Section 3 we explain how, although television was initially a luxury good, it became widespread relatively quickly and was included by ISTAT in baskets of goods by from 1953 onward.

as the local average treatment effect (LATE) on compliers. Each assumption is examined in detail, supported by institutional context and empirical evidence to reinforce the credibility of the 2SLS estimation.

5.3 Economic quantification

Both empirical strategies imply that a plausibly exogenous organised crime presence reduces the TV license fee compliance rate. Taking as reference column (4) of Table 2, this estimate implies a reduction in the mean outcome of 1.8 percentage points over a decade, which consequently means an average loss in state revenue of roughly 47.5€ million in real terms.[30] This economic cost for the state is relevant for two reasons. First, as mentioned above, the magnitude of this quantification is likely a lower-bound estimate. Second, and connected to the first point, this reflects the direct loss of missing revenues from the TV license fee. Galbiati and Zanella (2012) shows that tax evasion has a positive social multiplier, implying a contagious feature. Hence, although this is beyond the capability and focus of this paper, we can conjecture that TV license fee evasion may be connected with the evasion of other taxes which are more economically driven, like income tax.

6 Robustness checks

6.1 Population heterogeneity

From Table A2, it is evident that the forced resettlement policy targeted more populous and urbanised municipalities as destinations. Besides the tests described so far, this fact invites additional scrutiny along this dimension. Hence, we conduct the following empirical exercises in Table A4. In column (1), we add as a control the squared population in 1950 interacted with year fixed effects, while in column (2), we exclude municipalities which had populations of over 250,000 in 1950.[31] The coefficient remains identical to that of Table 2, The coefficient remains identical to that of Table 2, providing evidence that our estimates are not purely driven by a

[30]Total revenues without the effect of organised crime, but with tax evasion, are computed as $\overline{TV\,Fee_t} * \overline{\sum_i Families_t} * \overline{TVComplianceRate_{it}} = 125.92€ * 11'407'528 * 0.53045 = 761'957'437€$. Total revenues with the effects of organised crime and tax evasion are then $\overline{TV\,Fee_t} * \overline{\sum_i Families_t} * \overline{TVComplianceRate^{OC}_{it}} = 125.92€ * 11'407'528 * (0.53045 - 0.018) = 736'101'568€$. The difference between the two is $25'855'868€$. Note that $(25'855'868/761'957'437) * 100 = 3.39\%$. We deflated $\overline{TV\,Fee_t}$ with the consumer price index with 2009 as a base.

[31]We follow the ISTAT classification. This leads to the exclusion of eight municipalities: Rome, Milan, Turin, Genova, Bologna, Florence, Trieste and Venice (https://finanzalocale.interno.gov.it.).

few big urban centres.

To analyse the role of population and urbanisation in more detail, we interact the forced resettlement policy DiD variable with two separate categorical variables. First, in column (3) of Table A4, we interact it with a variable that divides the population in 1950 into four categories: small cities (value 1, between 0 and 1,999 inhabitants), medium-small cities (value 2, between 2,000 and 9,999 inhabitants), medium-large cities (value 3, between 10,000 and 99,999 inhabitants), and large cities (value 4, more than 100,000 inhabitants). Second, in column (4) of Table A4, we interact it with a variable that divides population density in 1950 into quartiles. The omitted category refers to small municipalities with population density between 0 and the first quartile. Both columns show that municipalities with a relative high degree of inhabitants (population density) drive our estimates. In particular, small (with low population density) municipalities exhibit a positive coefficient, while all the other are negative and have higher magnitudes. Hence, we can conclude that our estimates, excluding small municipalities, are homogeneous along the population dimension.

6.2 Propensity score matching

To further address potential imperfections in the design and application of the forced resettlement law, we replicate the analysis with a sub-sample resulting from a PSM strategy.[32] While reducing the sample size, this approach maximises similarity in terms of the probability of a municipality being designated as a destination. We employ nearest neighbour matching via probit estimation with common support and five neighbours. We use the following variables in the matching procedure: population (1930, 1950), population density (1950), elderly index (1950), illiteracy index (1950), home ownership index (1950), employment rate in agriculture, industry, commerce and tertiary sectors (1950), altitude, and area. These are the unbalanced municipal covariates shown in Table A2. Further, we add the number of employees by two-digit sector (1950) and the number of firms by two-digit sector (1950) (Pinotti and Stanig, 2016). The resulting sample exhibits no significant disparity between the matched treated and untreated municipalities regarding the included background characteristics, as reported in Table A5, demonstrating the balance between these two groups. Moreover, Figure A3 shows the matching support and overlap in the distribution of the estimated probability of being exposed to the instrument for both the exposed and not exposed groups. Replicating the main anal-

[32]We used `psmatch2` command in Stata proposed by Leuven and Sianesi (2003).

ysis for these selected municipalities, Table A6 qualitatively confirms the static effect as well the results derived by the dynamic specification as reported in Figures A4 and A5. Lastly, we test the sensitivity to different matching techniques. In Table A7 we employ nearest-neighbour matching with three and seven neighbours, then switch to radius matching, and then to kernel matching.[33] Overall, the results remain valid.

7 Potential mechanisms

7.1 Economic and criminal activity

Exploring potential mechanisms, we first analyse how organised crime affects the local economy and criminal activity. Previous literature has already documented its detrimental effect on the economy (Pinotti, 2015) as it distorts the allocation of resources (Di Cataldo and Mastrorocco, 2021), especially in strategic sectors like construction (Scognamiglio, 2018). By infiltrating these sectors, they can exert control to secure illicit gains and simultaneously intensify criminal practices, including extortion and labour racketeering (Gambetta, 1993; Bandiera, 2003; Dipoppa, 2023), further undermining economic development and institutional integrity. Table 4 reports the results for the economic and criminal effect.[34] Related to economic activity, it shows that most coefficients are not significant, except those for the construction and mining sectors, which are significant and positive. Specifically, municipalities exposed to the forced resettlement policy registered an additional 0.293 and 8.388 firms in mining and manufacturing, respectively, over a decade. These correspond to a respective increase of 17% and 23%, respectively. Alongside these pieces of evidence, we observe a rise in the number of news reports mentioning extortion and labour racketeering activities by 9.1 and 7.3 percentage points over a decade. These findings are even more visible when implementing the DiD dynamic specification (Figure 6), which also indicates a modest increase in manufacturing activity. Overall, our estimates confirm that organised crime activities—including both illegal and legitimate business—affect the economy, significantly reshape local incentives and have important implications for local governance and public trust. These results can be interpreted in three ways. Firstly, the infiltration in those sectors creates the ideal conditions for the establishment of illegal cartels, reducing competition

[33]For both types, the histogram of the estimated propensity scores (not reported and available upon request) shows a notable overlap.

[34]We measure extortion and labour racketeering criminal activity by identifying keywords related to the two activities within the news reports we collected about organised crime.

and enabling economic advantage over suppliers or demanders. This influence can be exerted directly, through mafia-controlled firms, or indirectly, through extortion, intimidation, and control of existing business (Mirenda et al., 2022; Piemontese, 2023; Arellano-Bover et al., 2024). As a result, local population is hurt by the criminal consequences of these activities, which make it harder for individuals and businesses to thrive. This, in turn, leads to a decrease in tax compliance, as the resulting economic difficulties make it more challenging for businesses and individuals to meet their tax obligations. Secondly, as people are compelled to pay the mafia for "protection", organised crime effectively replaces the state in terms of tax collection and, to some extent, in the provision of public goods, such as security (Gambetta, 1993; Schneider and Enste, 2000). This informal system undermines the perceived role of the state, reducing the motivation to comply with formal taxation. Thirdly, citizens may also feel less inclined to pay taxes to a government that appears unable to enforce the law or offer effective protection (Besley, 2020). If the state cannot counteract mafia influence or guarantee public safety, the value of complying with formal tax obligations diminishes. In this way, organised crime not only substitutes state functions but also erodes public trust, leading to lower tax compliance as individuals and businesses question the return on their contributions to the formal system.

7.2 Change in values and trust in institutions: discussion

A closely related mechanism to the shift in local incentives caused by organised crime is the change in law-abiding citizens' values and their perception that institutions can be trusted. Exposure to criminal activities can lead individuals to assign less importance to civic honesty and pro-social behaviours, increasing the prevalence of dishonest and individualistic behaviour. Previous studies show that corruption and dishonest behaviours like tax evasion are contagious, spreading through communities and affecting collective norms and behaviours (Galbiati and Zanella, 2012; Gulino and Masera, 2023). As discussed in subsection 7.1, the infiltration of organised crime into local economies and the weakening of the state can make the mafia appear more reliable than formal institutions, further eroding trust in government and public services. Unfortunately, the non-representative nature of the available survey data at the municipality level prevents us from empirically testing this channel.[35] However, the theoretical link between

[35]ITANES offers publicly available survey data with questions about, among other issues, the level of trust in institutions, major social problems (including tax evasion and crime), and reasons for not voting, which include protest. However, ITANES is not intended to be representative at the municipality level, and the number of municipalities identified is low (942 vs 5,509 in the main analysis). A valid alternative to ITANES is the ISTAT survey on aspects of families' daily lives. Unfortunately, this data is only publicly available at the regional level,

mafia activity, change in values, and decline in institutional trust remains an important potential mechanism that merits further investigation.

7.3 Community characteristics and compliance: heterogeneity

Organised crime may influence tax compliance through differences in the social resilience of municipalities. To explore this possibility, we examine whether the estimated effect varies with baseline (1950) municipal characteristics commonly associated with civic capital—specifically, illiteracy rates, homeownership rates, age structure, and newspaper readership. We construct interaction terms using a median split for each variable.[36] As shown in Table 5, the effect of mafia presence on tax compliance appears more pronounced in municipalities with younger populations (col. 1), lower homeownership rates (col. 2), and higher levels of provincial newspaper readership (col. 4). While these results should be interpreted with caution due to the limitations of the proxies, they offer suggestive evidence that the erosion of civic capital may be more pronounced in contexts with weaker social cohesion or higher media exposure.

7.4 Migration

Lastly, a shift in population composition through migration could be a potential mechanism through which organised crime affects TV license fee compliance. In response to the economic boom of the Centre-North and its increased demand for unskilled labour, transplanted criminal organisations favoured migration to take advantage of the new arrivals (Dipoppa, 2023). This substantial wave of migrants may have effectively changed the composition of the population and reduced civic capital.[37] To explore this mechanism, we would ideally need municipal-level data on migration flows, such as an arrival-departure matrix. Unfortunately, data is not available at this detailed level. However, to partially test this mechanism, we exploit data on arrival and departures at the provincial level. First, we look at the additional effect of migration,

which is thus too aggregated given our context.

[36]As discussed in sub-section 3.4 and shown in Table A2, municipalities exposed to the forced resettlement policy differ significantly along several baseline characteristics, including the illiteracy, homeownership, and elderly indices. These variables have been linked to social cohesion and civic engagement in previous work. For instance, low homeownership is associated with weaker local attachment and lower participation in collective action (DiPasquale and Glaeser, 1999), and younger cohorts tend to show less tolerance for institutional failure and lower civic trust when exposed to corruption (Daniele et al., 2023). Moreover, high exposure to crime-related media may heighten distrust in institutions, potentially weakening compliance norms (Mastrorocco and Minale, 2018). While these measures are imperfect proxies, they offer a starting point to explore how the erosion of civic capital might differ across communities.

[37]The Italian North-South divide in terms of social and civic capital dimensions is well documented in the related literature (Durante et al., 2024, for example).

interacting the share of migrants from the provinces of the South to those of the Centre-North with the resettlement policy variable. Second, to refine this aggregate measure, we restrict the provinces of the South from which resettlers departed to those with a contemporary mafia index (Calderoni, 2011) higher than the median, within the South. Table 6 shows that these interactions, though negative, yield coefficients that are not statistically significant. Hence, at least at the aggregate level, we exclude that migration, combined with the forced resettlement policy, has an additional effect on the reduction in TV license fee compliance.

8 Conclusion

Organised crime is a topic of growing interest in economics, but more research is needed to explore its links to civic capital and general tax compliance. This paper addresses this gap by using historical and novel data sources to examine the impact of long-term exposure to organised crime on civic capital in Italy, specifically focusing on the Centre-North region. To address endogeneity concerns related to the presence of organised crime, we leverage the forced resettlement policy as an exogenous shock in a DiD setting.

Our findings highlight that prolonged exposure to the mafia significantly reduces the TV license fee compliance rate. This effect is statistically robust and economically relevant, and survives a series of robustness tests. Regarding potential mechanisms, we first find that municipalities exposed to the forced resettlement laws have more firms in strategic sectors for organised crime infiltration such as construction, as well as more episodes of extortion and labour racketeering. We also explore whether the effect varies across municipalities with different baseline characteristics related to civic capital—such as age, homeownership, and readership— while provincial migration does not exhibit similar heterogeneity. While these heterogeneous patterns are not conclusive and should not be interpreted as evidence of causal mechanisms, investigating these channels more directly remains an important avenue for future research.

This study establishes a novel link between organised crime and tax compliance. Further, it underlines the significant impact of long-term exposure to organised crime, even in regions outside its traditional strongholds. This suggests that transplanted criminal organisations can be as effective as their native counterparts in eroding civic capital and tax compliance. Our research advances scholarly understanding of the consequences of organised crime in this regard, highlighting it as a crucial subject for further investigation. Importantly, the implications of this study extend beyond Italy, offering valuable lessons for policymakers in other regions, including European states that have recently, been experiencing increased organised crime infiltration.

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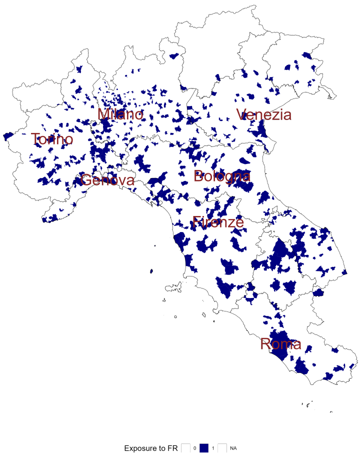
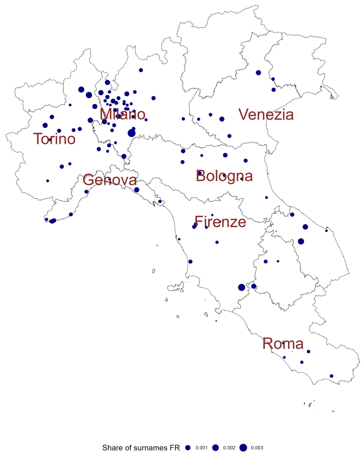
Figures and Tables

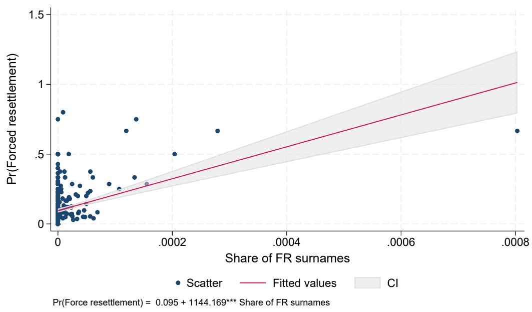
Figure 1: Geographical distribution of the forced resettlement policy and its persistence and their correlation.



(a) Forced resettlement distribution



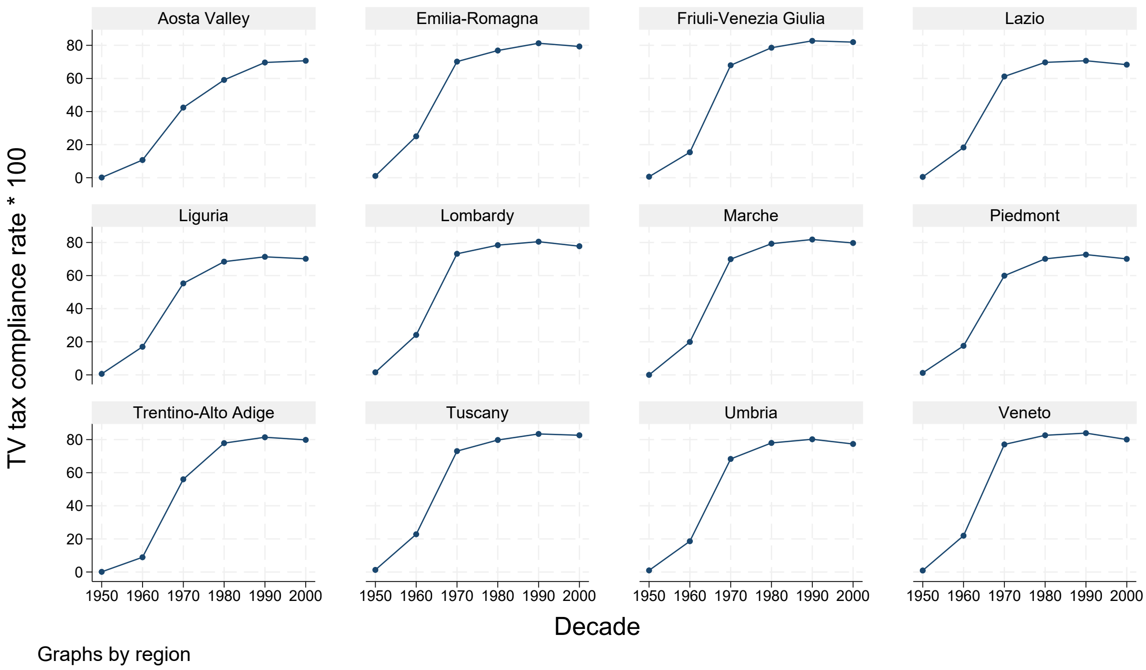
(b) Share of FR surnames of today surnames



(c) Correlation between (a) and (b)

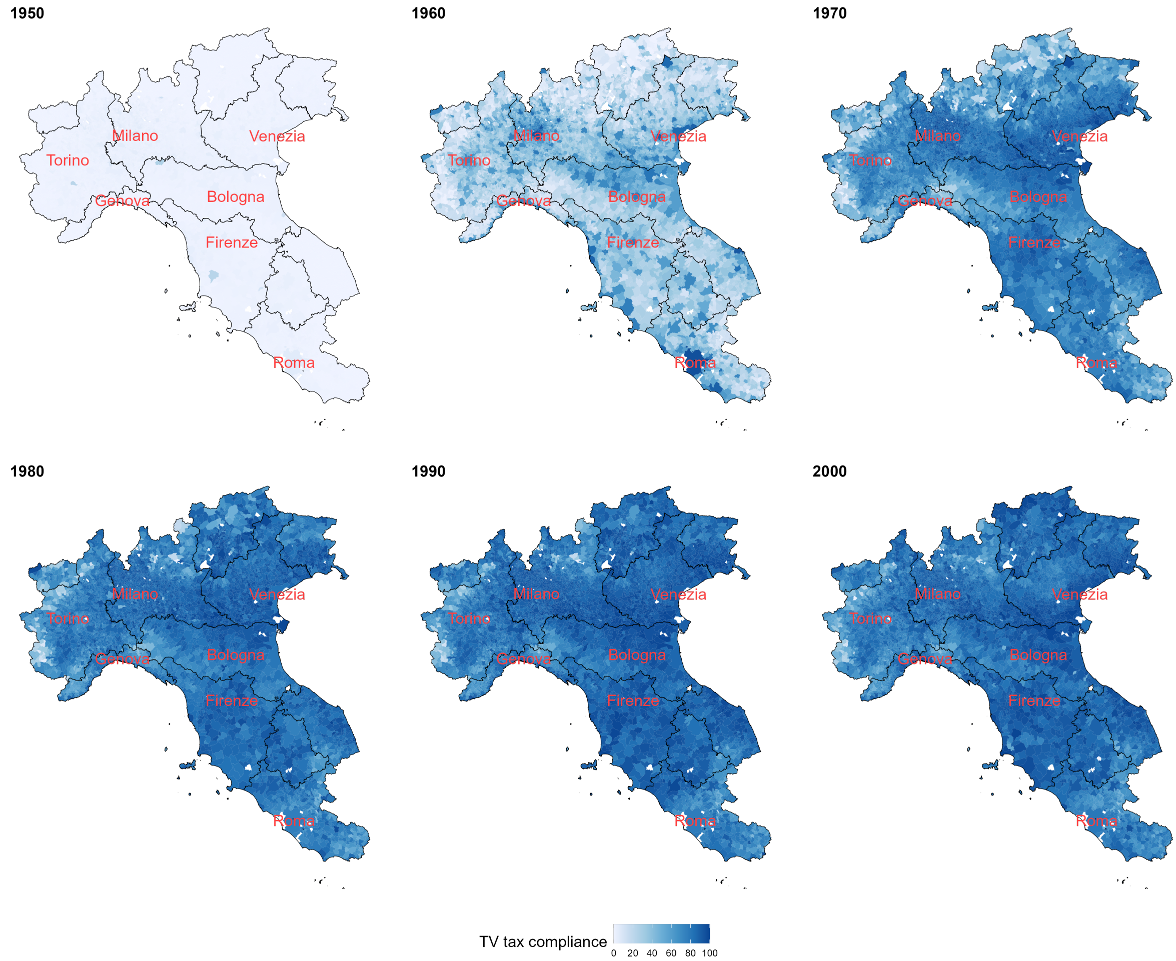
Notes. These maps show (a) the geographical distribution of forced resettlers receiving municipalities, (b) the share of forced resettlers surnames on nowadays surnames, and (c) shows the correlation between the two measures.

Figure 2: Evolution of TV tax compliance rate over time, by region



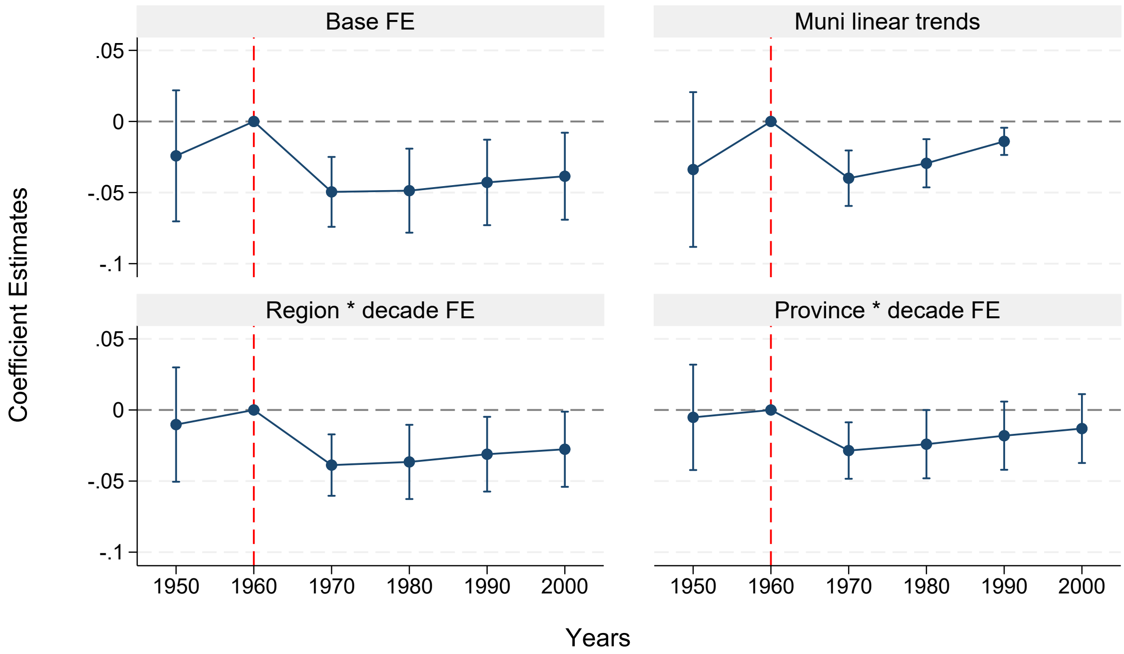
Notes. These plots show the evolution of TV tax compliance over time, by region.

Figure 3: Geographical distribution of TV tax compliance, by decade.



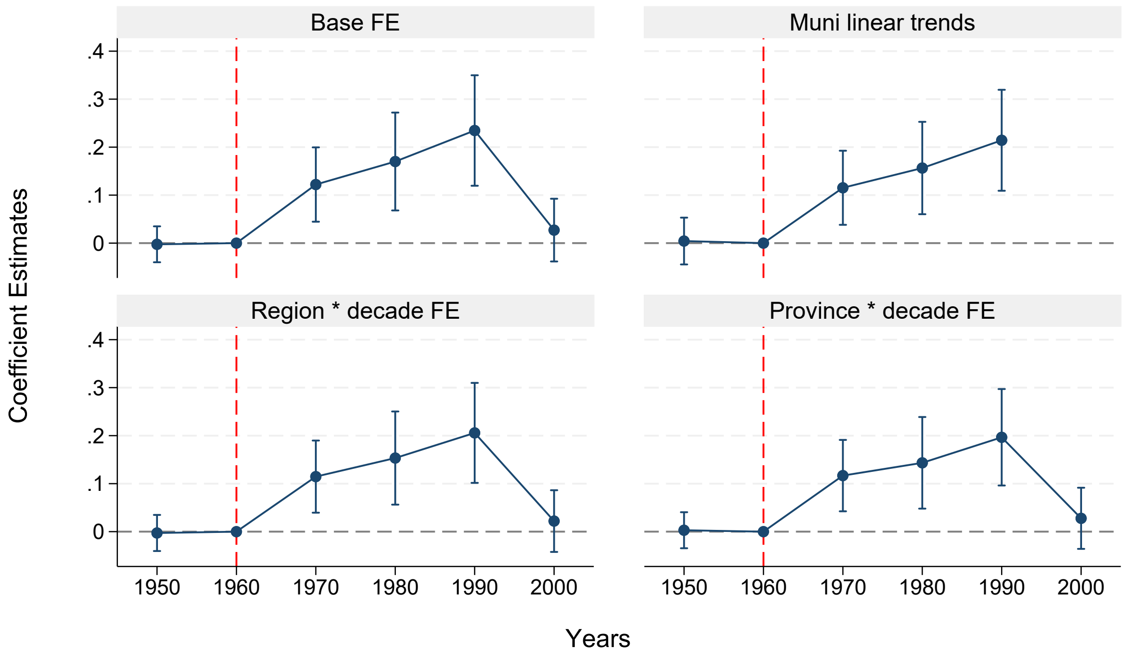
Notes. These maps show the geographical distribution of TV tax compliance in blue and by decade, with darker municipalities exhibiting higher values.

Figure 4: Forced resettlement and TV tax compliance. Event study specification.



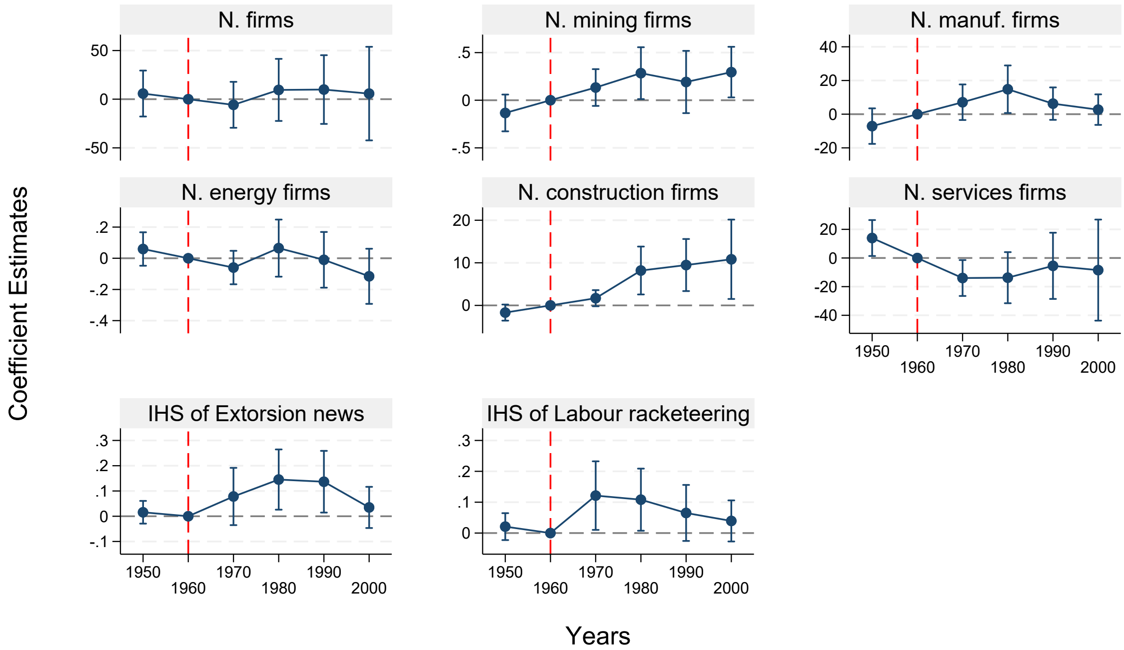
Notes. These plots show the event study specification of the reduced form that relates the forced resettlement DiD and the TV tax compliance, following Equation 2. Each sub-plot varies in the set of fixed effects that includes. The omitted decade is 1960.

Figure 5: Forced resettlement and organised crime news. Event study specification.



Notes. These plots show the event study specification of the first stage that relates the forced resettlement DiD and the number of news about organised crime, conceptually following Equation 2. Each sub-plot varies in the set of fixed effects that includes. The omitted decade is 1960.

Figure 6: Forced resettlement economic development and criminal activity. Event study specification.



Notes. These plots show the event study specification of the reduced form that relates the forced resettlement DiD and outcomes related to the local number of firms by sector and the number of news about organised crime containing keywords related to extortion and labour racketeering, conceptually following Equation 2. Each sub-plot varies in the set of fixed effects that includes. The omitted decade is 1960.

Table 1: Descriptive statistics of main variables.

	N	Mean	SD	Min	Max
Organised crime presence					
IHS of Mafia news	32994	0.30	0.89	0	8.73
Confino	32994	0.091	0.29	0	1
TV tax compliance					
TV tax compliance	32994	53.0	32.5	0	93.2
Migration					
Share migrants from South	32994	0.034	0.035	0	0.23
Share migrants from South (MI)	32994	0.022	0.022	0	0.14
Municipality demographics					
Population	32994	6234.1	45012.9	31	2840259
Pop. density	32994	230.9	430.7	1.04	9659.8
Elderly index	32994	111.3	112.1	6.90	4150
Avg. household size	32994	3.15	0.75	1.24	8.63
Owned house index	32994	67.6	17.5	0.67	100
Educ. gender gap	32994	139.0	71.2	0	2640.3
Illiterate index	32994	2.58	3.81	0	37.1
Municipality econ. characteristics					
LF participation rate	32994	51.2	6.81	20.2	89.6
Share emp. agric.	32994	25.1	23.4	0	100
Share emp. industr.	32994	42.5	17.9	0	95.6
Share emp. terz.	32994	19.5	11.6	0	81.0
Share emp. comm.	32994	13.5	6.96	0	88.3
N. of firms	32958	342.2	2187.8	0	169633
N. of firms in mining	16493	1.62	4.80	0	188
N. of firms in manuf.	32773	76.6	357.5	0	22220
N. of firms in energy	21286	1.41	3.64	0	143
N. of firms in constr.	32930	36.1	162.4	0	17944
N. of firms in services	32958	206.6	1548.9	0	122673

Notes. This table shows the descriptive statistics of the main variables at our disposal in the analysis. 'MI' stands for Mafia Index and refers to migrants from a region in the South with a MI higher than the median (Calderoni, 2011). 'LF' stands for labour force.

Table 2: Forced resettlement and TV tax compliance.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
$Confino_{i,t}$	-0.033**	-0.050***	-0.028**	-0.018*
	(0.014)	(0.013)	(0.012)	(0.011)
N	32994	32994	32994	32994
Mean TV tax	53.045	53.045	53.045	53.045
Controls	✓	✓	✓	✓
Municipality and decade FE	✓	✓	✓	✓
Municipality linear trends		✓		
Region * decade FE			✓	
Province * decade FE				✓

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. Depending on the specification, we include municipality and decade fixed effects, municipality linear trends, region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Organized crime news and TV tax compliance.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
	Panel A - OLS			
IHS(Mafia$_{i,t}$)	-0.011***	-0.008***	-0.009***	-0.009***
	(0.004)	(0.003)	(0.003)	(0.003)
	Panel B - 2SLS			
IHS(Mafia$_{i,t}$)	-0.235*	-0.251***	-0.226*	-0.153
	(0.121)	(0.091)	(0.117)	(0.100)
	[-0.629,-0.033]	[-0.602,-0.117]	[-0.628,-0.033]	[-0.474, 0.026]
N	32994	32994	32994	32994
KP F-Stat	12.970	11.731	11.971	11.460
CD F-Stat	50.548	36.873	42.738	39.059
NR Upper bound CI	-0.019	-0.027	-0.018	0.004
FS coeff.	0.140***	0.199***	0.125***	0.120***
Mean TV tax	53.045	53.045	53.045	53.045
Controls	✓	✓	✓	✓
Municipality and decade FE	✓	✓	✓	✓
Municipality linear trends		✓		
Region * decade FE			✓	
Province * decade FE				✓

Notes: Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The endogenous variable, *Mafia$_{i,t}$*, refers to the IHS of the number of news related to the mafia in municipality i at t. The instrumental variable, *Confino$_{i,t}$*, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. *Panel A* shows the OLS estimates, while *Panel B* shows the 2SLS estimates. The Kleibergen-Paap (KP) and Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to *Panel B* estimates. Upper bound confidence intervals are constructed following Nevo and Rosen (2012). In *Panel B* confidence intervals based on inversion of the Anderson-Rubin test are shown in square brackets. Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), all interacted with decade dummies. Depending on the specification, we include municipality and decade fixed effects, municipality linear trends, region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Forced resettlement, economic development and criminal activity.

	N firms	*N firms mining*	*N firms manuf.*	*N firms energy*	*N firms constr.*	*N firms services*	*IHS(share news extorsion)*	*IHS(share news labor racket)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Confino_{i,t}$	1.945	0.293**	11.266	-0.060	8.388***	-17.375	0.091**	0.073**
	(20.466)	(0.137)	(7.141)	(0.076)	(2.808)	(12.338)	(0.037)	(0.030)
N	32958	15738	32736	20406	32928	32958	32994	32994
Mean Y	342.177	1.655	76.700	1.438	36.120	206.571	1.512	0.963
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Municipality and decade FE	✓	✓	✓	✓	✓	✓	✓	✓
Prov * decade FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Dependent variables: the number of firms; the number of firms in mining; the number of firms in manufacturing; the number of firms in energy; the number of firms in construction; the number of firms in services; the IHS of the share of news related to extorsion; the IHS of the share of news related to labour racketeering. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. We include municipality and decade fixed effect. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Forced resettlement, municipality characteristics and provincial readership.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
$Confino_{i,t}$	0.009	0.028	-0.010	-0.038**
	(0.016)	(0.023)	(0.013)	(0.016)
$Confino_{i,t}$ * *Eld. Ind.* $<$ *med.*$_{i,t0}$	-0.054***			
	(0.020)			
$Confino_{i,t}$ * *Own house. Ind.* $<$ *med.*$_{i,t0}$		-0.076***		
		(0.025)		
$Confino_{i,t}$ * *Ill. Ind.* $<$ *med.*$_{i,t0}$			-0.017	
			(0.022)	
$Confino_{i,t}$ * *Newspapers per cap* $<$ *med.*$_{p,t0}$				0.023
				(0.022)
N	32994	32994	32994	32994
Mean TV tax	53.045	53.045	53.045	53.045
Controls	✓	✓	✓	✓
Municipality and decade FE	✓	✓	✓	✓
Region * decade FE				✓
Province * decade FE	✓	✓	✓	

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. It is then interacted with a series of dummy variables equal to one if a municipality has a value of that variable lower than the median in the 1950. The variables are elderly index (1950, column 1), illiterate index (1950, column 2), owned house index (1950, column 3) and the number of newspapers sold per capita in the province (1980, column 4). For this last variable, we use the regional median rather than the median of the whole sample. Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. When analysing the interaction with elderly index (1950), illiterate index (1950) or owned house index (1950), we remove the variable from the list of controls. Depending on the specification, we include municipality and decade fixed effects and either region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Forced resettlement and TV tax compliance. Migration heterogeneity.

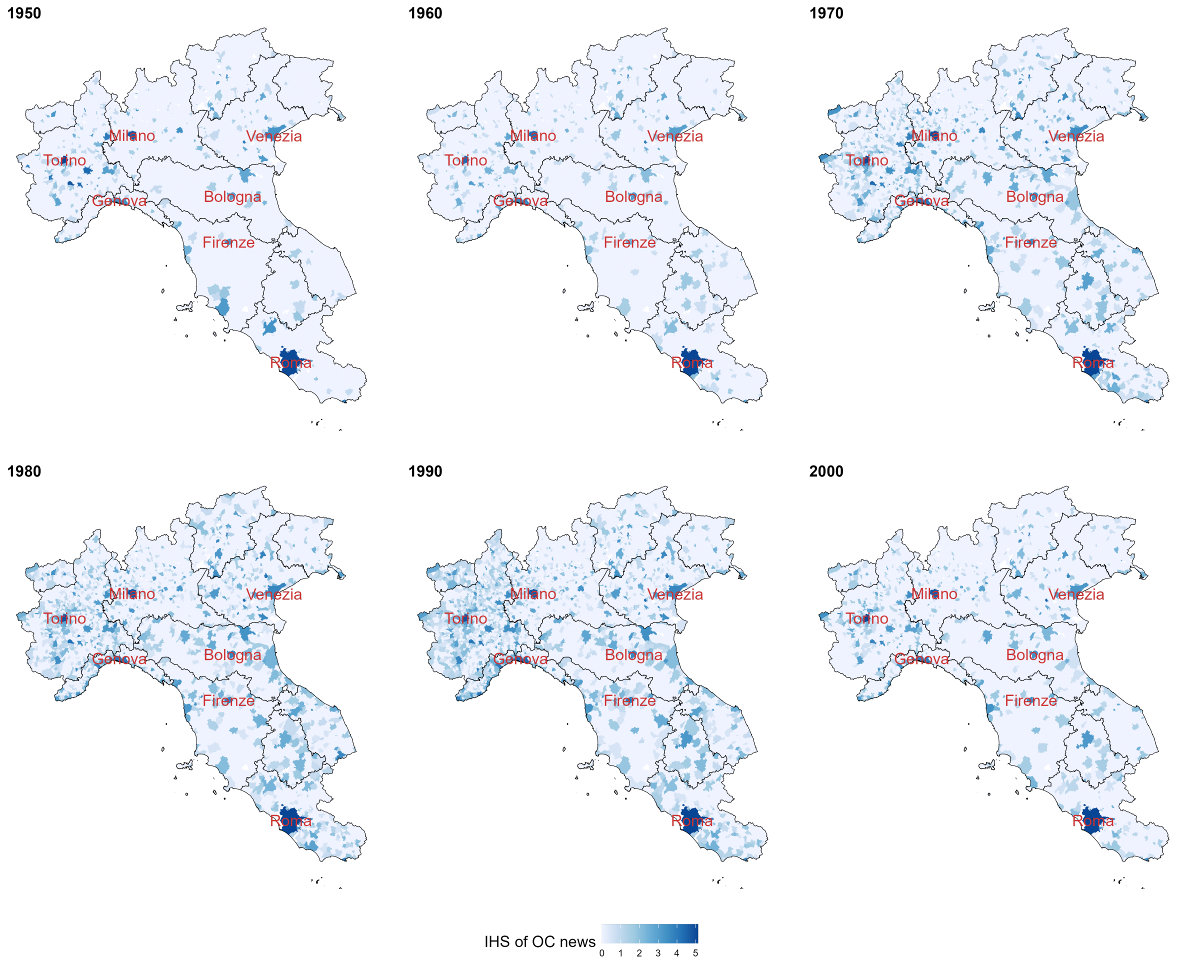
	IHS(TV tax compliance rate)		
	(1)	(2)	(3)
$Confino_{i,t}$	-0.028**	-0.022	-0.022
	(0.012)	(0.015)	(0.015)
$Confino_{i,t}$ * $Share\ South\ Migr_{p,t}$		-0.190	
		(0.232)	
$Confino_{i,t}$ * $Share\ South\ MI\ Migr_{p,t}$			-0.314
			(0.348)
N	32994	32994	32994
Mean TV tax	53.045	53.045	53.045
Controls	✓	✓	✓
Municipality and decade FE	✓	✓	✓
Region * decade FE	✓	✓	✓

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. Column (1) reports the main estimates. Column (2) interacts $Confino_{i,t}$ with the share of migrants arriving from the South macro-area to province p at decade t. Column (3) interacts $Confino_{i,t}$ with the share of migrants arriving from a province in the South of Italy with a Mafia Index (MI) higher than the median (Calderoni, 2011) to province p at decade t.Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. We include municipality and decade fixed effects. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Appendix A Main Appendix

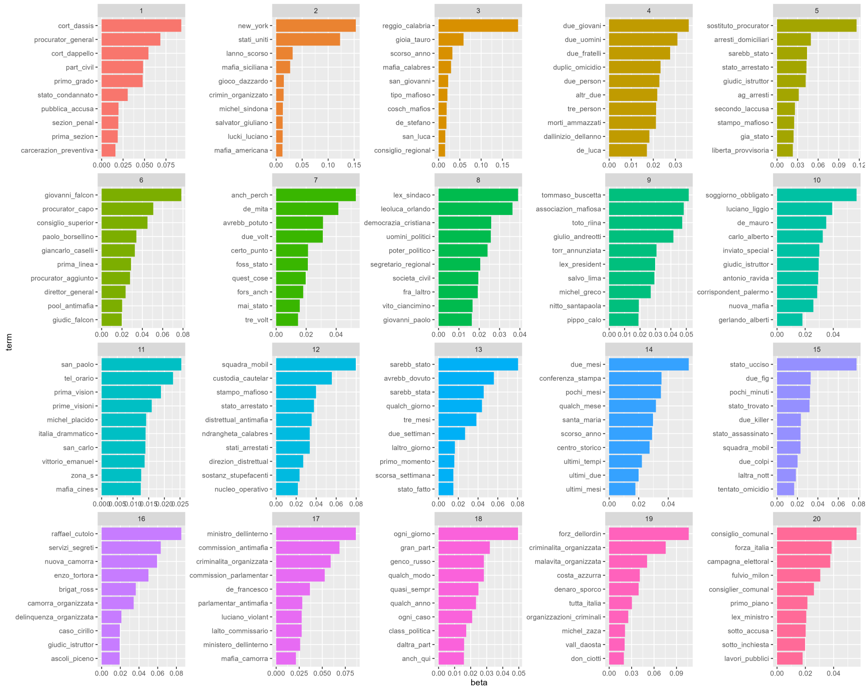
A.1 Figures

Figure A1: Geographical distribution of the IHS of organised crime related news, by decade.



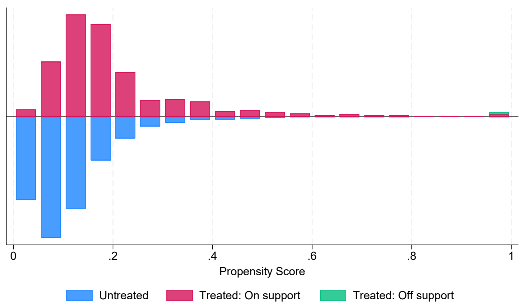
Notes. These maps show the geographical distribution of news related to organised crime in blue and by decade, with darker municipalities exhibiting higher values. The organised crime news variable is IHS transformed.

Figure A2: Topics of organised crime-related news extracted via an LDA model.

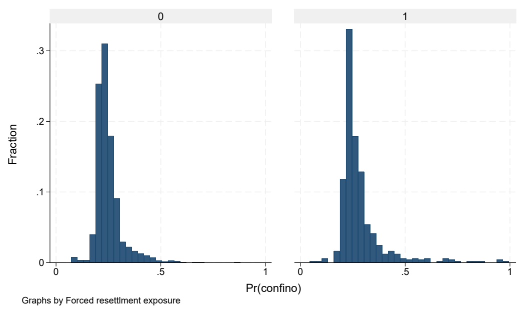


Notes. This plot shows the top 20 most frequent topics obtained by an LDA model.

Figure A3: Propensity score matching sample diagnostics.



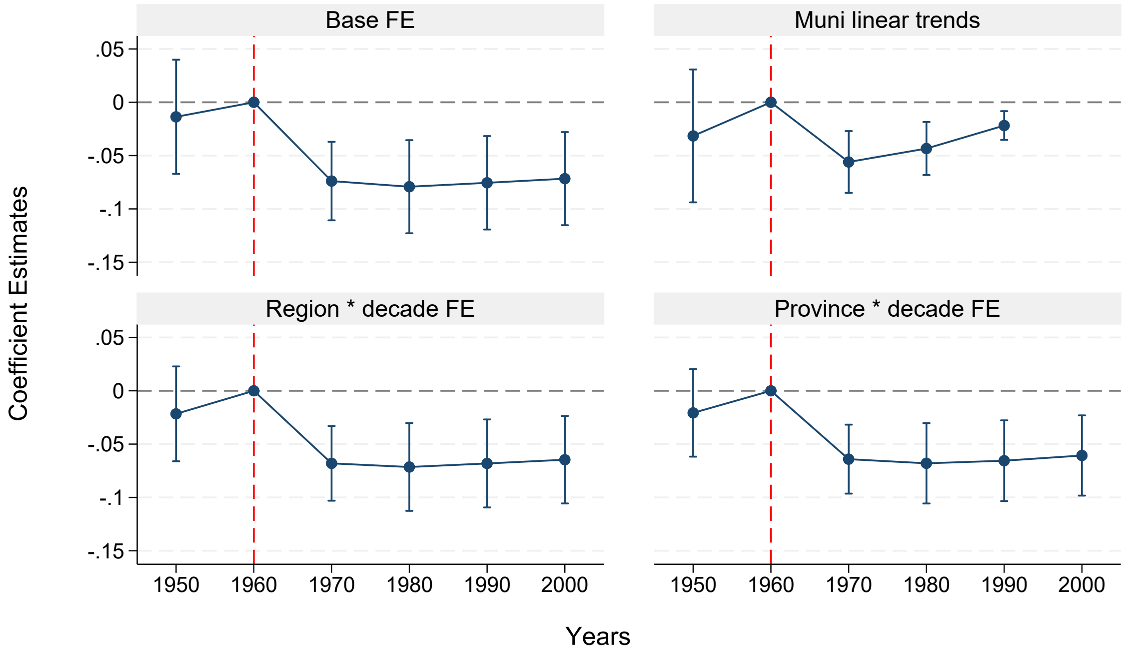
(a) Matching support



(b) Probability of exposure

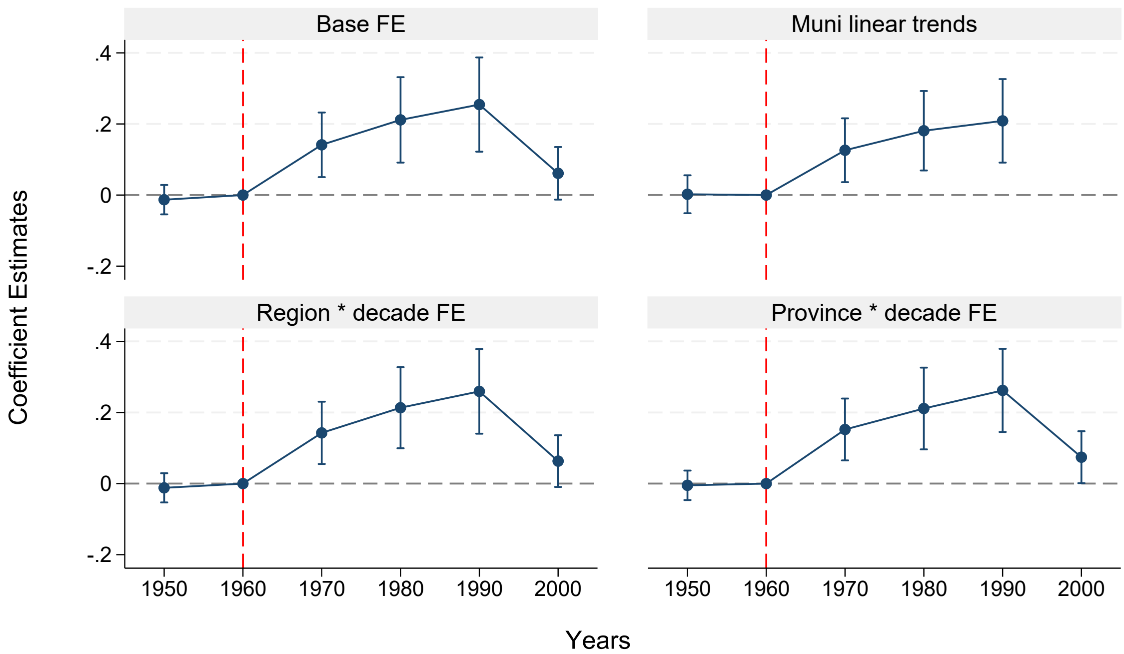
Notes. These plots show the support of the PSM strategy in (a), and the distribution of the probability of exposure to the forced resettlement policy of matched observations (b).

Figure A4: Forced resettlement and TV tax compliance. Event study specification. PSM sample.



Notes. These plots show the event study specification of the reduced form that relates the forced resettlement DiD and the TV tax compliance, following Equation 2, restricting the sample to the one resulting from the PSM strategy. Each sub-plot varies in the set of fixed effects that includes. The omitted decade is 1960.

Figure A5: Forced resettlement and organised crime news. Event study specification. PSM sample.



Notes. These plots show the event study specification of the first stage that relates the forced resettlement DiD and the number of news about organised crime, conceptually following Equation 2, restricting the sample to the one resulting from the PSM strategy. Each sub-plot varies in the set of fixed effects that includes. The omitted decade is 1960.

A.2 Tables

Table A1: Correlation between mafia news indicator and confiscations dummies.

	Confisc. $Overall_{i,1980\text{-}2020}$ (1)	(2)	*Confisc.* $Firms_{i,1980\text{-}2020}$ (3)	(4)	*Confisc.* $Real\ Estate_{i,1980\text{-}2020}$ (5)	(6)
	Different periods					
$Mafia_{i,1950\text{-}1990}$	0.076***	0.032***	0.050***	0.018***	0.072***	0.032***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)
N	5509	5499	5509	5499	5509	5499
Mean outcome	0.171	0.171	0.049	0.049	0.158	0.158
	Overlapping periods, with Mafia from 1950s					
$Mafia_{i,1950\text{-}2000}$	0.079***	0.033***	0.052***	0.020***	0.075***	0.034***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
N	5509	5499	5509	5499	5509	5499
Mean outcome	0.171	0.171	0.049	0.049	0.158	0.158
	Overlapping periods, with Mafia from 1980s					
$Mafia_{i,1980\text{-}2000}$	0.069***	0.029***	0.044***	0.016***	0.065***	0.030***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
N	5509	5499	5509	5499	5509	5499
Mean outcome	0.171	0.171	0.049	0.049	0.158	0.158
SLL FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓

Notes: Dependent variables: a dummy equal to one if a municipality ever experienced a confiscation; a dummy equal to one if a firm registered in a municipality has ever been confiscated; a dummy equal to one if a real estate in a municipality has ever been confiscated. The endogenous variable, $Mafia_{i,t}$, refers to the log of the number of news related to the mafia in city i. We average it over three different periods: between 1950s and 1990s; between 1950s and 2010s; between 1980s and 2000s.Controls include city population (1936, 1950), population density (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area. All columns include local labor markets areas fixed effects. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Balance table by forced resettlement law.

Variable	Not-FR	FR	Diff. (FR-NFR)
Population (1930)	3929.062	15866.213	11937.1514***
	(8377.0967)	(72712.9062)	(1093.7496)
Population (1950)	4022.163	19610.111	15587.9473***
	(9975.2891)	(1.055e+05)	(1554.2584)
Pop. density (1950)	174.968	339.450	164.4827***
	(206.4826)	(562.9448)	(12.1775)
Elderly index (1950)	49.644	46.634	-3.0095**
	(28.5761)	(21.7593)	(1.3132)
Avg. household size (1950)	4.030	4.076	0.0461
	(0.7842)	(0.7402)	(0.0366)
Owned house index (1950)	55.138	39.968	-15.1699***
	(22.0247)	(16.3781)	(1.0109)
Educ. gender gap (1950)	170.232	163.249	-6.9832
	(104.5616)	(52.5631)	(4.7304)
Illiterate index (1950)	5.833	7.360	1.5277***
	(5.8259)	(5.7509)	(0.2727)
LF participation rate (1950)	56.180	55.836	-0.3439
	(7.5769)	(6.6674)	(0.3514)
Share emp. agric. (1950)	52.074	43.017	-9.0566***
	(24.9707)	(24.8838)	(1.1697)
Share emp. industr. (1950)	32.089	37.393	5.3040***
	(21.5932)	(21.6717)	(1.0122)
Share emp. comm. (1950)	8.436	9.978	1.5424***
	(5.0569)	(4.8878)	(0.2362)
Share emp. terz. (1950)	7.413	9.614	2.2007***
	(5.3018)	(7.0442)	(0.2569)
Altitude	0.342	0.217	-0.1252***
	(0.3011)	(0.1849)	(0.0137)
Area	0.302	0.524	0.2222***
	(0.3916)	(0.7979)	(0.0208)
IHS Mafia news (avg.50s/00s)	0.367	0.838	0.4713***
	(0.8737)	(1.3567)	(0.0435)
Observations	5008	501	5509

Notes. The table assesses the balancedness of forced resettlement exposure along a set of pre-instrument characteristics. * p<0.10, ** p<0.05, *** p<0.01.

Table A3: Forced resettlement and TV tax compliance. Other specifications.

	(1)	(2)	(3)	(4)
$Confino_{i,t}$	-0.117***	-0.018*	-0.024**	-0.015
	(0.013)	(0.010)	(0.011)	(0.009)
N	33054	32496	30294	32994
Mean Y	53.034	53.858	52.881	73.526
Municipality and decade FE	✓	✓	✓	✓
Prov * decade FE	✓	✓	✓	✓
Baseline controls		✓	✓	✓
Contemp. controls	✓			
Poisson estimator		✓		
No mani. dest.			✓	
TV+radio				✓

Notes. Column (1) employs contemporaneous controls. Column (2) employs a Poisson pseudo-likelihoo estimator and avoid the IHS transformation on the dependent variable. Column (3) excludes those municipalities that exhibit any organised crime related news in the 1950 decade. Column (4) uses as dependent variable the IHS of the ratio of the number of TV licences over the number of households * 100, which is summed with the ratio of the number of radios over the number of households.In all columns but in column (1), controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. We include municipality and decade fixed effects. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Forced resettlement and TV tax compliance. Population heterogeneity.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
$Confino_{i,t}$	-0.018*	-0.018*	0.089*	0.082**
	(0.011)	(0.011)	(0.050)	(0.035)
$Confino_{i,t}$ * $Pop_{i,t}$ = 2			-0.101**	
			(0.050)	
$Confino_{i,t}$ * $Pop_{i,t}$ = 3			-0.164***	
			(0.054)	
$Confino_{i,t}$ * $Pop_{i,t}$ = 4			0.137	
			(0.200)	
$Confino_{i,t}$ * $Pop\ Dens_{i,t}$ = 2				-0.090**
				(0.038)
$Confino_{i,t}$ * $Pop\ Dens_{i,t}$ = 3				-0.122***
				(0.039)
$Confino_{i,t}$ * $Pop\ Dens_{i,t}$ = 4				-0.147***
				(0.039)
N	32994	32946	32994	32994
Mean TV tax	53.045	53.035	53.045	53.045
Municipality and decade FE	✓	✓	✓	✓
Prov * decade FE	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓
Quadratic baselin Pop.	✓			
No muni. > 250k		✓		
Pop int.			✓	
Pop Dens int.				✓

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. Column (1) additionaly controls for the quadratic of population in (1950). Column (2) excludes municipalities with baseline population (1950) higher than 250'000. In Column (3) $Confino_{i,t}$ is then interacted with a categorical variable related to baseline population (1950), $Pop_{i,t}$. $Pop_{i,t} = 1$ gathers municipalities between 0 and 1'999; $Pop_{i,t} = 2$ gathers municipalities between 2'000 and 9'999; $Pop_{i,t} = 3$ gathers municipalities between 10'000 and 99'999; $Pop_{i,t} = 4$ gathers municipalities with population higher than 100'000. The reference category is $Pop_{i,t} = 1$. In Column (4) $Confino_{i,t}$ is then interacted with a categorical variable related to baseline population density (1950), $Pop\ Dens_{i,t}$. $Pop\ Dens_{i,t} = 1$ gathers municipalities between 0 and the first quartile; $Pop\ Dens_{i,t} = 2$ gathers municipalities between the first and the second quartile; $Pop\ Dens_{i,t}$ gathers municipalities between the second and the third quartile; $Pop\ Dens_{i,t}$ gather municipalities with population higher than the third quartile. The reference category is $Pop\ Dens_{i,t} = 1$. Unless specified, controls include municipality population (1930) population (1950, not in column 3), population density (1950, not in column 4), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude and area, all interacted with decade dummies. Depending on the specification, we include municipality and decade fixed effects, municipality linear trends, region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A5: Balance table by forced resettlement law post PSM.

Variable	FR	Not-FR	p value
Population (1930)	12526	9628.4	0.251
Population (1950)	15398	10855	0.252
Pop. Density (1950)	315.11	295.82	0.410
Owned house index (1950)	39.713	38.104	0.118
Illiterate index (1950)	7.372	7.686	0.415
Elderly index (1950)	46.264	45.825	0.763
Share emp. agric. (1950)	42.855	43.407	0.736
Share emp. industr. (1950)	37.567	36.672	0.525
Share emp. terz. (1950)	9.630	10.054	0.378
Share emp. comm. (1950)	9.950	9.869	0.809
Altitude	0.217	0.201	0.177
Area	0.527	0.504	0.641
N. firms - 30 (1950)	126.17	114.5	0.384
N. firms - 31 (1950)	46.024	42.827	0.594
N. firms - 40 (1950)	14.357	12.348	0.446
N. firms - 50 (1950)	2.0582	1.8474	0.478
N. firms - 60 (1950)	155.62	150.93	0.724
N. firms - 70 (1950)	19.655	18.952	0.774
N. firms - 80 (1950)	5.4241	4.096	0.260
N. firms - 90 (1950)	35.014	33.041	0.700
N. employees - 30 (1950)	361.63	366.67	0.874
N. employees - 31 (1950)	212.11	195.85	0.463
N. employees - 40 (1950)	97.962	93.321	0.587
N. employees - 50 (1950)	22.088	22.194	0.979
N. employees - 60 (1950)	268.65	261.23	0.705
N. employees - 70 (1950)	78.943	77.979	0.920
N. employees - 80 (1950)	27.278	27.537	0.964
N. employees - 90 (1950)	58.767	64.295	0.559
Aosta Valley	0.002	0.003	0.710
Lombardy	0.291	0.271	0.492
Trentino-Alto Adige	0.004	0.007	0.546
Veneto	0.077	0.069	0.620
Friuli-Venezia Giulia	0.019	0.018	0.923
Liguria	0.060	0.074	0.382
Emilia-Romagna	0.121	0.128	0.754
Tuscany	0.117	0.130	0.543
Umbria	0.025	0.017	0.393
Marche	0.070	0.087	0.363
Lazio	0.054	0.051	0.840

Notes. The table shows the balancedness by forced resettlement exposure along a set of pre-instrument characteristics after the PSM strategy. * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Forced resettlement and TV tax compliance. PSM sample.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
$Confino_{i,t}$	-0.059***	-0.069***	-0.050***	-0.050***
	(0.023)	(0.020)	(0.019)	(0.017)
N	11202	11202	11202	11202
Mean TV tax	53.034	53.034	53.034	53.034
Municipality and decade FE	✓	✓	✓	✓
Municipality linear trends		✓		
Region * decade FE			✓	
Province * decade FE				✓

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. The sample is restricted to one resulting from a nearest neighbout matching strategy. The matching strategy is based on the following variables: population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude, area, the number of employees by 2-digit sector (1950) and the number of firms by 2-digit sector (1950). Depending on the specification, we include municipality and decade fixed effects, municipality linear trends, region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A7: Forced resettlement and TV tax compliance. Alternative PSM samples.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
$Confino_{i,t}$	-0.032*	-0.063***	-0.140***	-0.141***
	(0.018)	(0.016)	(0.015)	(0.015)
N	8832	12948	23010	23100
Mean TV tax	57.391	56.986	54.762	54.789
Municipality and decade FE	✓	✓	✓	✓
Province * decade FE	✓	✓	✓	✓
PSM type	NN3	NN7	Radius	Kernel

Notes. Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The main variable of interest, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. In column (1) the sample is restricted to one resulting from a nearest neighbour matching strategy with 3 neighbours, in column (2) with 7 neighbours, in column (3) from a kernel (epanechnikov) strategy, and in column (4) from a radius strategy. The matching strategy is based on the following variables: population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), altitude, area, the number of employees by 2-digit sector (1950) and the number of firms by 2-digit sector (1950). We include municipality and decade fixed effects and province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Appendix B Data sources details

B.1 Mafia news

Article example. We present some examples of an article related to organised crime in our extracted sample.

2 Martedì 1 Aprile 1975

I roghi di S. Maria Maggiore

Due disastri in un mese: è la mafia?

DAL NOSTRO INVIATO

S. Maria Maggiore, 1 aprile.

Le indagini sullo spaventoso rogo dell'*Excelsior*, che ha fatto quindici vittime, sembrano entrare in un vicolo cieco. Manca ancora una spiegazione plausibile e ufficiale sulle origini del sinistro. Si attendono le conclusioni della commissione di funzionari, dei vigili del fuoco e della protezione civile, che è stata insediata, subito dopo la sciagura, dal ministro Gui.

I tecnici della commissione hanno compiuto numerosi sopralluoghi fra le rovine dell'albergo e hanno prelevato reperti che sono stati definiti « *molto significativi* ».

Domani tornerà a Santa Maria Maggiore anche il perito giudiziario, ing. Notarbartolo, che è stato incaricato di eseguire rilievi tecnici dal sostituto procuratore della Repubblica di Verbania, dott. Claudio De Angelis, che dirige l'inchiesta. La sua relazione sarà messa a confronto con quella della commissione ministeriale.

Fra gli inquirenti, si sta facendo strada la convinzione che l'incendio sia divampato per cause accidentali. Lo ha detto chiaramente il capo della Criminalpol del Piemonte, dott. Montesano. Tutte le piste finora battute si sono rilevate infruttuose; le tracce che sembravano promettere interessanti sviluppi hanno perso consistenza. Alla caserma dei carabinieri di Santa Maria Maggiore, il colonnello Patti e il capitano Ambrosio hanno interrogato decine di persone: protagonisti, superstiti, soccorritori. Si è scavato nei loro ricordi alla ricerca di qualche particolare che possa far luce sulla misteriosa tragedia.

Se l'incendio è doloso, le ipotesi che trovano maggior credito sono quella di una vendetta, maturata nel mondo delle agenzie di viaggio che convogliano in Italia i turisti stranieri, o anche quella di un piromane isolato, che avrebbe agito sotto la spinta di un folle impulso distruttivo.

Secondo le voci che circolano in paese, la mafia avrebbe allungato i suoi tentacoli alle principali località turistiche e il rogo dell'*Excelsior* sarebbe nient'altro che un momento della guerra che si è scatenata fra cosche concorrenti. Questo spiegherebbe anche l'incendio che esattamente un mese prima aveva devastato l'altro grande albergo di Santa Maria Maggiore, lo « *Sporting* ». E' vero che lo « *Sporting* » era chiuso, ma avrebbe dovuto riaprire entro pochi giorni proprio per ospitare comitive di francesi. Ci sono coincidenze che fanno meditare. Lo « *Sporting* » bruciò il 27 febbraio; all'*Excelsior* le fiamme sono divampate il 27 marzo.

Adriano Velli

1) The article talks about a hotel set on fire in the city of Santa Maria Maggiore, in the province of Verbania, Piedmont. *«Is it the mafia? [...] The investigations into the appalling fire at the Excelsior, which claimed fifteen lives, seem to hit a dead end. There is still no plausible and official explanation of the origins of the accident. [...] According to rumours circulating in the country, the mafia would have extended its tentacles to the main tourist resorts, and the burning of the Excelsior would be nothing more than a moment of the war that has been unleashed between rival gangs.»*

Nuovo sanguinoso episodio in provincia di Milano

Sparano dall'auto e uccidono un barista Eliminato perché rimodernava il locale?

(Dal nostro corrispondente)

Milano, 25 giugno.

Un uomo è stato ucciso la scorsa notte all'interno di un bar gestito dalla moglie da 2 rivoltelalte esplose da bordo di una Bmw che si è subito dileguata. Il delitto secondo i carabinieri non ha alcun movente politico anche se la vittima rivestiva la carica di vice presidente della sezione combattenti e reduci di Lainate piccolo paese a una ventina di chilometri da Milano: si tratta con tutta probabilità di una vendetta, anche se forse gli assassini volevano semplicemente limitarsi ad un avvertimento e solo per pura fatalità i proiettili hanno colpito l'uomo.

La vittima è Salvatore Primerano, di 52 anni, originario di Catanzaro, operaio in uno stabilimento della zona. Il drammatico fatto di sangue è avvenuto poco prima di mezzanotte. Nei locali del «Cral, Circolo combattenti e reduci» gestito dalla moglie della vittima, Rosa Donato, di 48 anni. La donna in quel momento era in casa, proprio sopra il bar nello stabile di via Madonna 15, in pieno centro del paese.

Da qualche giorno il locale era chiuso al pubblico per permettere di eseguire lavori di restauro che a quanto pare avevano trovato l'opposizione dei titolari degli altri bar della zona che temevano la concorrenza: il «Circolo combattenti e reduci» è un locale «pulito» frequentato da gente

va parlando con i due operai sui lavori che avrebbero dovuto essere ultimati lunedì prossimo. La porta a vetri smerigliati del Cral era chiusa e dall'esterno si vedeva solo la luce accesa. Improvvisamente davanti allo stabile di via Madonna 15 si è fermata una Bmw bianca con a bordo 4 persone: da uno dei finestrini è apparsa una mano arma-

scorsi l'operaio avesse ricevuto larvate minacce.

Secondo gli inquirenti la morte del Primerano sarebbe dovuta a pura fatalità: gli sparatori avevano forse solo intenzione di lanciare il loro «avvertimento» perché dalla strada non potevano vedere all'interno e stabilire dove si trovassero i due imbianchini

e il marito della titolare del Cral. Secondo i carabinieri non c'è altra spiegazione. Le indagini comunque si sono estese anche in Calabria per frugare nel passato della vittima ed accertare eventuali suoi collegamenti con la malavita e in particolare con la «'ndrangheta».

Gino Mazzoldi

Milano. Salvatore Primerano, la moglie Maria Rosa Donato e la figlia Concetta

2) The article reports a new bloody episode in the province of Milan regarding a shoot from the car and the kill of a bartender as evidence of 'ndrangheta: *«A man was killed last night in a bar run by his wife by two revolvers that exploded from the edge of a BMW which immediately vanished. According to the carabinieri, the crime has no political motive even if the victim held the position of vice president of the combatants and veterans section of Lainate, a small town about twenty kilometres from Milan: it is in all probability a matter of revenge, although perhaps the killers simply wanted to limit themselves to a warning and only by sheer fatality did the bullets hit the man. The victim is Salvatore Primerano, 52 years old, originally from Catanzaro, a worker in a factory in the area. [...] he never got involved in politics even though he had been appointed vice president of the Fighters and Veterans section of Lainate. This task and the fact that his wife owned the CRAI had created jealousy in the environment as more and more customers flocked to the place, deserting the other bars in the*

area.[...]»

(3) The article discusses Turin's new face at fiery midnight where there are episodes of clan vendettas, female and male prostitution, drug selling: *«[...]"Black Turin" regained nine-column headlines in the news pages, then the paragraphs diminished, the news became thin and cold, and everyday life resumed with its sad undertows. I have to condense in this article an overly nourished series of information on Turin, which has "become different". It is explained to me: there is the prostitution racket, the drug racket, the third of the fruit and vegetable markets, mediated by Neapolitan experiences; here we are at the fourth of extortion; here we are at the fifth of the kidnappings; here we are at the sixth, of the building industry, where labour, concrete and piles of illicit money guarantee. They are forms of the mafia of the Camorra, which followed the great immigrations of the 1950s and, within a generation, managed to proliferate and take root in favourable terrain.[...]»*


IL VOLTO INQUIETANTE DELLA CITTÀ "DIVENTATA UN'ALTRA,,
A Torino, mezzanotte di fuoco
Vendette di clan, prostituzione femminile e maschile, droga venduta davanti alle scuole come castagnaccio: si moltiplica una fauna miserabile e violenta


L'operazione della Guardia di finanza a Sanremo e Saint Vincent
CENTINAIA DI AGENTI ARMATI DI MITRA HANNO BLOCCATO I CLIENTI DEI CASINO'

4) The article reports on two police operations (in Aosta and Sanremo) in gambling houses. *«Sanremo. The city seems to be under siege. Checkpoints on the highway, at the railway station, on the outskirts. Interior Minister Scalfaro's offensive against the mafia and the laundering of "dirty" money inside the casino is shocking the coast.[...] "They are looking for three men - the rumours chased each other - who would have been found hiding on a boat or die during the night they would have had time to avoid the encirclement and escape from Sanremo aboard a yacht". Who are they: mafiosi, money lenders, former elements linked to the "'ndrangheta" who would have laundered money from kidnappings at the roulette tables? For now, nothing is known about the official. The hypotheses overlap. The second blitz in the history of the Sanremo casino opens disturbing questions.[...]»*

Latent Dirichlet allocation details. In our analysis, we apply the latent Dirichlet allocation (LDA) method to identify latent topics from a corpus of newspaper articles reporting mafia-related events. We provide some details about this methodology.

First, we pre-process the text of the news article to standardise it by removing punctuation and extra spaces, and converting all text to the same format (lowercase). A comprehensive list of stopwords, including general and context-specific terms, is defined to exclude irrelevant words from the analysis. The text data is then structured into a corpus, a format that facilitates linguistic and content analysis. We perform tokenisation to break the text into individual units while removing URLs, numbers, and symbols. Words are reduced to their root forms through stemming. Further, we filter out stopwords, and we convert the text into sequences of two-word phrases (bigrams) to capture meaningful patterns. We exclude empty or invalid documents. A document-feature matrix (DFM) is then created to represent the frequency of terms across documents. Lastly, we remove terms with extremely low or high frequencies to focus the analysis on the most informative words.

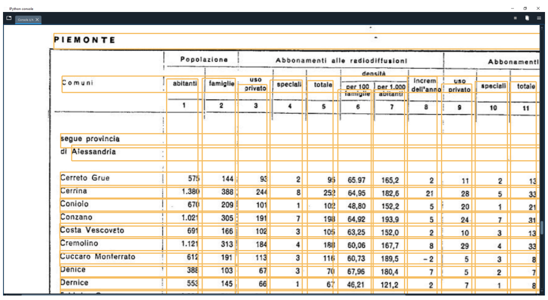
We then employ the LDA, a probabilistic model, to uncover underlying themes in the text. The number of topics is set to 20, and hyperparameters are configured to control the distribution of topics within documents and terms within topics. LDA assumes that documents are composed of a mixture of topics and that topics are composed of a mixture of words. The algorithm iteratively estimates the probability distributions that describe the importance of terms within topics and the relevance of topics within documents. These distributions are derived using Gibbs sampling, a method for obtaining random samples from a probability distribution (Gentzkow et al., 2019).

The term-topic relationships are analysed to extract the most representative terms for each topic, which are visualised through bar plots in Figure A2 in the main Appendix. These plots highlight the key terms associated with each topic, providing a clear view of the semantic structure.

B.2 Forced resettlement document

Figure A6: Example of the list of relocated people transmitted to the Committee by the Italian Ministry of the Interior on February 13th, 1974.

B.3 TV license fee scraping



We deployed a Python script structured as follows to digitise the yearly PDFs received from RAI containing municipality-level information on the TV license fee compliance rate. First, each page from a PDF containing the TV license fee compliance rate, the number of TV licenses and the number of households at the municipal level in a given year, is transformed into an image. Then, the rotation of each image is adjusted to correct some inappropriately scanned pages. Then, we exploit `layoutparser` (Shen et al., 2021) functionalities to create a grid that identifies the values of each variable of interest for a given municipality. A visual example of this grid is the figure in this subsection. Lastly, after having compiled a list of the municipality and a list of relevant variables on a page, we perform a loop that extracts values for a variable and a municipality within each grid point. We have created a series of Python scripts to automate the whole process, taking into account changes in the layout of the RAI PDFs over time.

Appendix C Validating IV design

In this appendix, we present the main results of the IV design and describe the conditions for which the forced resettlement policy is a valid instrument and for the IV estimand to be interpreted as a weighted average of local treatment effects on the compliers, i.e., the Local Average Treatment Effect (LATE). We discuss each assumption and support them with arguments based on institutional details and empirical evidence. Lastly, we propose corrections for possible distortions.

Table A8: Organized crime news and TV tax compliance.

	IHS(TV tax compliance rate)			
	(1)	(2)	(3)	(4)
	Panel A - OLS			
IHS($Mafia_{i,t}$)	-0.011***	-0.008***	-0.009***	-0.009***
	(0.004)	(0.003)	(0.003)	(0.003)
	Panel B - 2SLS			
IHS($Mafia_{i,t}$)	-0.235*	-0.251***	-0.226*	-0.153
	(0.121)	(0.091)	(0.117)	(0.100)
	[-0.629,-0.033]	[-0.602,-0.117]	[-0.628,-0.033]	[-0.474, 0.026]
N	32994	32994	32994	32994
KP F-Stat	12.970	11.731	11.971	11.460
CD F-Stat	50.548	36.873	42.738	39.059
NR Upper bound CI	-0.038	-0.095	-0.006	0.003
FS coeff.	0.140***	0.199***	0.125***	0.120***
Mean TV tax	53.045	53.045	53.045	53.045
Controls	✓	✓	✓	✓
Municipality and decade FE	✓	✓	✓	✓
Municipality linear trends		✓		
Region * decade FE			✓	
Province * decade FE				✓

Notes: Dependent variable: the IHS of the ratio of the number of TV licences over the number of households * 100. The endogenous variable, $Mafia_{i,t}$, refers to the IHS of the number of news related to the mafia in municipality i at t. The instrumental variable, $Confino_{i,t}$, is a dummy equal to 1 if a municipality i received a confinato. It is equal to 0 pre-1970 and equal to 1 from 1970 onward. *Panel A* shows the OLS estimates, while *Panel B* shows the 2SLS estimates. The Kleibergen-Paap (KP) and Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to *Panel B* estimates. Upper bound confidence intervals are constructed following Nevo and Rosen (2012). In *Panel B* confidence intervals based on inversion of the Anderson-Rubin test are shown in square brackets. Controls include municipality population (1930, 1950), population density (1950), elderly index (1950), illiterate index (1950), owned house index (1950), and employment rate in agriculture, industry, commerce and tertiary (1950), all interacted with decade dummies. Depending on the specification, we include municipality and decade fixed effects, municipality linear trends, region or province * decade fixed effects, respectively. Municipality clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Relevance. From a qualitative point of view, forced resettlement represented a crucial boost to mafia transplantation, as discussed in Section 2. We provide quantitative evidence for the instrument's relevance, as is customary in instrumental variable strategies. Table A8 shows the coefficients of the first stage under different specifications, which are always statistically significant and positive. This is the sign that we would expect, as it shows that the forced resettlement law positively predicts the presence of organised crime. Across all the columns, the first stage coefficients change very little when we include additional combinations of fixed effects. Further, the table reports both the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F-statistics for weak identification, with values ranging from 12.970 to 11.460 and from 50.548 to 36.873, respectively. These point toward a solid and relevant first stage relationship. In particular, the robust KP F-statistic F is equivalent to the effective F-statistic of Olea and Pflueger (2013) in the case of a single instrument (Andrews et al., 2019). Additionally, we calculate the Anderson- Rubin confidence intervals, which are robust and efficient even in weak instruments, and report them below standard errors in brackets. Excluding column (4), all Anderson-Rubin confidence intervals remain negative. Lastly, we apply the methodology of Lee et al. (2022) to column (1) to estimate valid t-ratio inference for IV and report the results in Table A9.[38] The table shows that the coefficient of interest is statistically significant for the tf procedure at the 5% level, but not at the 1% level.[39] Overall, these pieces of evidence favour the strength of our IV strategy.

Table A9: Lee et al. (2022) valid t-ratio inference

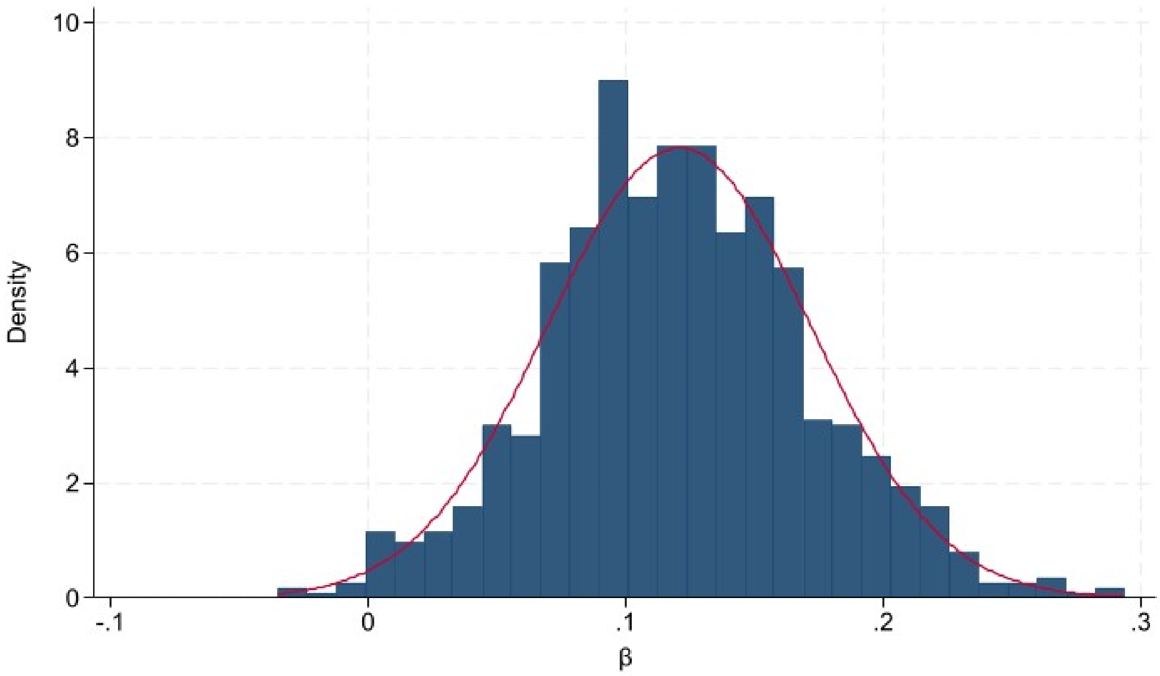
	5% Level	1% Level
Coefficient	-0.264	-0.264
Std. Err.	0.081	0.081
Crit. Val.	2.130	3.432
Adj. Std. Err.	0.087	0.107
Lower Bound	-0.435	-0.540
Upper Bound	-0.092	0.013
First-stage F-stat	52.151	52.151

Notes: This table applies the methodology from Lee et al. (2022) to estimate valid t-ratio inference for instrumental variables. The estimates the command works on is column (1) of Panel B of Table A8.

[38]The `tf` command does not converge with the additional fixed effects of columns (2), (3) and (4). It is worth mentioning that, for convergence issues, we removed one control, *Share emp. comm. (1950)* interacted with decade fixed effects. This is the reason why the coefficients between Table A9 and column (1) Panel B of Table A8 are not the same.

[39]5% level: $|-0.264/0.087| = 3.034 > 2.130$. 1% level: $|-0.264/0.107| = 2.467 < 3.432$.

Figure A7: Distribution of betas of the first stage. Monte Carlo simulation.



Monotonicity. To interpret IV estimates as LATEs, the monotonicity assumption must hold (Angrist and Imbens, 1994). This requires that the instrumental variable has an effect in the same direction on all affected municipalities, in our case positively. Although we cannot test this assumption directly, a common approach to checking whether an effect is homogeneous is to use a Monte Carlo simulation. Specifically, we can randomly draw a large number of subsamples (N = 1000), estimate the first-stage equation separately for each subsample, and then analyse the distribution of the estimated coefficients (Beta) by plotting the distribution and providing descriptive statistics. This exercise plausibly allows us to assess whether the correlation between the instrument and the endogenous variable is systematically present in N subsamples. We do so with the first stage of column (4) specification, which includes province multiplied by decade fixed effects. Figure A7 shows that the distribution of the coefficients of the first stage is consistently positive and centres around the value of 0.120. Overall, this exercise reassures us that the monotonicity assumption is valid in this case.

Strict exogeneity. While forced resettlement is a plausibly exogenous shock, it needs to be strictly exogenous, that is $Corr(C_{it},\ \epsilon_{it}) = 0$. As discussed in Section 2, judges likely chose destination municipalities for relocation which were far from mafia strongholds and in more developed areas, considering general criteria like the their locations, regions, and broader economic characteristics. However, it is unlikely that all the judges, located as they were at the head of courts in different provinces in the Southern regions of Italy, could accurately predict the developmental path of distant towns.

Table A10: Balance table by forced resettlement law.

Variable	Not-FR	FR	Diff. (FR-NFR)
Population (1930)	3929.062	15866.213	11937.1514***
	(8377.0967)	(72712.9062)	(1093.7496)
Population (1950)	4022.163	19610.111	15587.9473***
	(9975.2891)	(1.055e+05)	(1554.2584)
Pop. density (1950)	174.968	339.450	164.4827***
	(206.4826)	(562.9448)	(12.1775)
Elderly index (1950)	49.644	46.634	-3.0095**
	(28.5761)	(21.7593)	(1.3132)
Avg. household size (1950)	4.030	4.076	0.0461
	(0.7842)	(0.7402)	(0.0366)
Owned house index (1950)	55.138	39.968	-15.1699***
	(22.0247)	(16.3781)	(1.0109)
Educ. gender gap (1950)	170.232	163.249	-6.9832
	(104.5616)	(52.5631)	(4.7304)
Illiterate index (1950)	5.833	7.360	1.5277***
	(5.8259)	(5.7509)	(0.2727)
LF participation rate (1950)	56.180	55.836	-0.3439
	(7.5769)	(6.6674)	(0.3514)
Share emp. agric. (1950)	52.074	43.017	-9.0566***
	(24.9707)	(24.8838)	(1.1697)
Share emp. industr. (1950)	32.089	37.393	5.3040***
	(21.5932)	(21.6717)	(1.0122)
Share emp. comm. (1950)	8.436	9.978	1.5424***
	(5.0569)	(4.8878)	(0.2362)
Share emp. terz. (1950)	7.413	9.614	2.2007***
	(5.3018)	(7.0442)	(0.2569)
Altitude	0.342	0.217	-0.1252***
	(0.3011)	(0.1849)	(0.0137)
Area	0.302	0.524	0.2222***
	(0.3916)	(0.7979)	(0.0208)
IHS Mafia news (avg.50s/00s)	0.367	0.838	0.4713***
	(0.8737)	(1.3567)	(0.0435)
Observations	5008	501	5509

Notes. The table assesses the balancedness of forced resettlement exposure along a set of pre-instrument characteristics. * p<0.10, ** p<0.05, *** p<0.01.

To address potential imbalance in the municipalities' features, we formally investigate differences between municipalities which received forced resettlers and those which did not by performing a t-test on municipalities' characteristics in the pre-sample period. Table A10 shows the results of this exercise. It can be noted that a few variables exhibit statistically significant differences.[40] In particular, forced resettlers were relocated to bigger, more populated areas with stronger urban than agricultural sectors. To attenuate possible bias introduced by these variables, we include these as controls at baseline interacted with decade dummies. Then, conditional on these controls included in the regression and various combinations of fixed effect, the IV estimates capture the external variation, being orthogonal to ϵ_{it}. Moreover, to determine the extent to which our main findings are robust to moderate violations of the exogeneity assumption, we rely on the method developed by Nevo and Rosen (2012).[41] Specifically, it estimates the bounds of β of Equation 4, relaxing the exogeneity assumption.[42] In our case, only upper bounds are returned since the first stage coefficient is positive. The bounds are reported at the bottom of Table A8. They are all negative, except those in column (4), and are in line with the upper bound of Andreson-Rubin's confidence interval. These results are reassuring, even allowing for plausible amounts of imperfect exogeneity.

Exclusion Restriction. The IV approach also relies on the exclusion restriction; that is, the presence of forced resettlers only affects TV license fee compliance by affecting the spread of the mafia in the municipality, as measured through news reports relating to organised crime. The implementation of this policy was driven by law enforcement motives rather than the inherent characteristics of the receiving communities in the Centre-North and decisions within the criminal world. However, there is evidence that some notable figures within the criminal world were able to influence the decision about where they should be sent (Dipoppa, 2023). We argue that it is unlikely that most of the members of a criminal organisation could systematically influence the judges' decisions. Moreover, as depicted in Figure 1, the distribution of the forced resettlers in our dataset is relatively homogeneous. However, given the absence of guidelines for the judges to use when making their decisions, the qualitative evidence of manipulation of some judges' decisions, and the fact that civic capital does correlate with many aspects of society, we cannot claim that the forced resettlement law is as good as a randomised experiment. This is in line with Table A10, which highlights a set of variables for which municipalities exposed and not exposed to the forced resettlement policy are unbalanced. For instance, larger municipalities

[40]They are population (1930 and 1950), population density (1950), elderly index (1950) owned house index (1950), illiterate index (1950), the shares of employment in agriculture, industry, commerce and tertiary (1950), and geographical characteristics such as altitude and area.

[41]We use respectively the Stata command `imperfectiv`.

[42]They assume that 1) the correlation between the instrument and the error term exists and has the same sign as the correlation between the endogenous regressor and the error term; 2) that the instrument is less correlated with the error term than the endogenous regressor is.

may possess greater administrative capacity, potentially making the effects of resettlement less significant. Similarly, a higher illiteracy rate could reflect greater social vulnerability, while a lower homeownership rate might indicate higher mobility or economic instability, which could influence the dynamics of the response to the resettlement policy. Despite the following efforts in assessing the exclusion restriction assumption, these potential sources of bias inherently plague the IV identification strategy.

To assess whether the exclusion restriction is satisfied, we employ the newly developed method proposed by D'Haultfœuille et al. (2021), valid for binary instruments. The test suggests that the exclusion restriction holds since it does not reject the null hypothesis even at the 1% significance level.[43] However, to openly discuss eventual violations of the exclusion restriction, we apply the methodology presented in Conley et al. (2012), which allows us to test the sensitivity of the second stage coefficients of interest to controlled violations of the exclusion restriction.[44] We follow the union of confidence intervals (UCI) approach.[45] Namely, to estimate the confidence interval of β, we incrementally vary γ by a parameter δ, incrementing by intervals of 0.01 from 0 to 0.50 to generate increasingly more substantial violations of the exclusion restriction.[46] Figure A8 shows the results which plots the 90% confidence interval of the β, of the specifications in Table A8, equivalent to different values of δ.

When $\delta = 0$, where the exclusion restriction assumption holds perfectly. With $\delta > 0$, the confidence intervals expand progressively, including zero only when $\delta =\sim 0.19$ for (a), $\delta >\sim 0.50$ for (b), $\delta =\sim 0.19$ for (c) and $\delta = 0$ (d). Hence, taking as reference subplot (a), for our parameter of interest to become statistically insignificant and thus uninformative about the causal impact of organised crime on TV tax compliance, the direct effect of forced resettlement on TV tax compliance would have to be roughly one-fifth of the β.

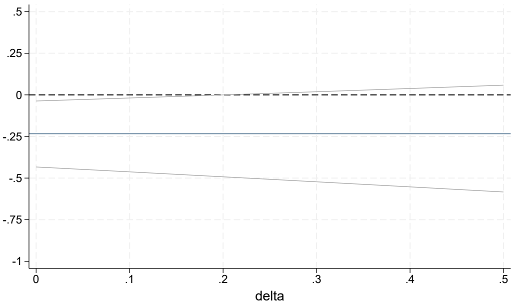
[43]We performed the test using Stata module `testex`. We computed the test for the specification of column (4) of Table A8. The estimated KS statistics is 2.908, and the associated p-value is 0.978

[44]We use the Stata command `plausexog`.

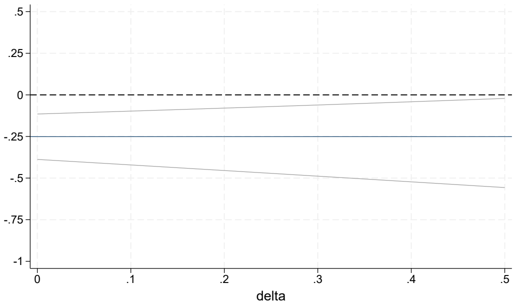
[45]Considering the following equations: $Y = \beta X + \gamma Z + \epsilon$ and $X = Z\Pi + V$, their method replaces the exact exclusion restriction assumption ($\gamma = 0$), by allowing $\gamma \neq 0$ and assess how it influences estimates of β. Unlike the local-to-zero approach, we follow the UCI approach because it does not require distributional assumptions, giving the most conservative interval estimates of β.

[46]$\gamma = \beta_{IV} * \delta$, where β_{IV} is equal to -0.153, the coefficient of column (4) of Table A8.

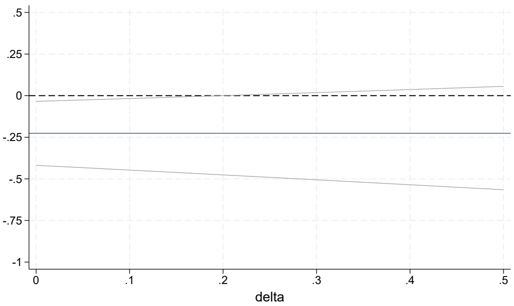
Figure A8: Sensitivity of inference about the effect of the instrument on violations of the exclusion restriction



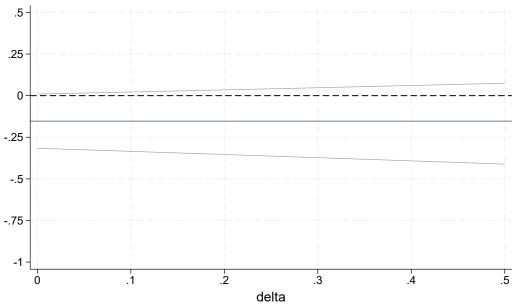
(a) Column (1) of Table A8



(b) Column (2) of Table A8



(c) Column (3) of Table A8



(d) Column (4) of Table A8

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