Soil consumption and organized crime: The case of the Italian region of Apulia*

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Abstract

Soil consumption is the increase in artificial land cover through anthropogenic activities. Its relationship with organized crime is important for economic and environmental reasons. We measure the effect of organized crime on soil consumption focusing on Apulia, an Italian region subject to recent mafia expansion. We present two empirical strategies, one relying on a conditional independence assumption and the availability of a rich set of controls, the other employing as instrument the forced resettlement program of mafia bosses during 1956–1995. Our findings show that the diffusion of organized crime causes a substantial increase in the amount of consumed soil.

Keywords: Soil consumption; organized crime; forced resettlement.

JEL classification codes: K42; Q24; R14.

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1 Introduction

Soil is a precious non-renewable natural resource that provides ecosystem services essential for life. Soil consumption is the increase in artificial land cover through urbanization, infrastructures, and other land developments that involve the removal of soil and its vegetation. Our paper investigates the effect of organized crime on soil consumption by focusing on the Italian region of Apulia, an interesting case of recent mafia development. Our main assumption is that organized crime plays a decisive role in determining land-use planning and soil consumption at the local municipality level due to the mutually beneficial relationship between the mafia and local politicians. This assumption is supported by evidence that local clans obtain economic advantages in the construction sector in exchange for their electoral support (De Feo & De Luca, 2017).

The relationship between soil consumption and organized crime is important for both economic and environmental reasons. One of them is carbon sequestration – a slow process in which carbon dioxide is removed from the atmosphere and stored in the soil. This ecosystem service is particular important in the current era because of the need to both combat and adapt to climate change (Lal, 2004; Foley et al., 2005). Indeed, soil stores more carbon than other terrestrial ecosystems (Ciais et al., 2014), but this process is quickly reversed if soil is consumed through urbanization and other artificial land developments. Another critical service provided by soil is water maintenance, which helps attenuate or prevent both flooding and the risk of water scarcity (Faccini et al., 2018; Saco et al., 2021). Additional ecosystem services include regulation of above-ground diversity, nutrient cycling, transformation of potentially harmful elements and compounds, and the capacity to resist sudden changes in pH levels (Wall et al., 2015, Greiner et al., 2017).

Soil consumption has raised many concerns and induced leading international institutions, such as the Food and Agriculture Organization (FAO) and the United Nations (UN), to promote actions intended to curb its growth. The FAO has repeatedly warned against the risk posed to the soil ecosystem services by intensive agriculture, deforestation, and urban sprawl. In 2012, FAO members countries and partners signed the Global Soil Partnership, a mechanism intended to promote sustainable soil management, while the UN declared 2015 to be the International Year of Soils to increase awareness and understanding of the importance of soil among decision makers and the civic society.

In recent decades, Europe has witnessed a steady increase in artificial land covering. The rate of increase has been more than twice the rate of population growth, a trend that is clearly unsustainable in the long run (European Environment Agency, 2023). To contrast this trend, the European Union approved in July 2023 the Nature Restoration Law, which requires member states to introduce by 2030 measures to restore 20% of their currently degraded ecosystems, in particular those with the most potential to capture and store carbon and to prevent and reduce the impact of natural disasters, raising the target to all degraded ecosystems by 2050.

Soil consumption appears to be particularly problematic in arid or semi-arid areas of Southern Europe. These areas are recognized as vulnerable to desertification because of the impact of land-use changes and associated climate variation induced by extensive urbanization and illegal construction activity (Salvati & Bajocco, 2011). At the same time, the construction industry has been shown to be a breeding ground for organized crime infiltration in these areas (Chiodelli, 2019; Mirenda et al., 2022) because of its market organization, which allows for large amounts of money to be laundered easily, and its regulatory framework, which assigns most responsibilities to the local level. In Italy, for instance, each municipality is the main decision-maker about territorial planning strategies, and the mafia infiltration within the local public authorities has often led to urban sprawl into surrounding rural areas, thereby overriding existing regulations (Scognamiglio, 2018).

Italy has historically been plagued by the conspicuous presence of mafia-type organizations (see, e.g., Acemoglu et al., 2020). Their presence has contributed to economic and social backwardness, depletion of social capital, and corruption of local institutions and business (Pinotti, 2015).

Italy has also experienced an intense consumption of soil (Fiorini et al., 2019). According to the latest 2022 annual report by the Italian National System for Environmental Protection (SNPA), the fraction of Italian land that is artificially covered grew by about 5.7% between 2006 and 2021, from 6.7% to 7.1%. During the same 15-year period, the Italian population grew by about 1.7%, from 58.1 million to 59.1 million. As a result, artificial land covering per capita increased by about 4% between 2006 and 2021. This growth has not been uniform throughout the country: Italian regions show heterogeneous patterns that depend upon a variety of factors other than their different physical morphology.

Among the Italian regions, Apulia stands out because of an increase in artificial land covering per capita of about 12.5% between 2006 and 2021, the second largest in the country (the largest is the neighboring region of Basilicata, with an increase of about 15.3%) and more than three times the Italian average of 4%. Apulia is a region of nearly 4 million inhabitants in the South-Eastern end of the Italian peninsula, bordered by the Adriatic Sea to the east and the Ionian Sea to the South and South-West. Like other Mediterranean regions, in the last few decades Apulia has undergone a rapid economic transformation away from agriculture, accompanied by important changes in agricultural practices. These processes have transformed the Apulian landscape and generated soil degradation issues, making the region particularly prone to land desertification (Ladisa et al., 2012). It is worth noting that several other Central and Northern Italian regions have not been immune from this phenomenon and its consequences. For example, the Northern region of Emilia-Romagna has recently suffered from dramatic floods which have arguably been made worse by soil consumption.

Apulia also represents a peculiar success story of mafia transplantation. The presence of organized crime in this region is a phenomenon that only emerged in recent decades. The Apulian *Sacra Corona Unita*, often referred to as the "fourth mafia", started operating between the late 1970s and the early 1980s. While the origins of the other three prominent forms of organized crime in Italy (*Cosa Nostra*, *Camorra* and *'Ndrangheta*) are deeply rooted in the historical, political, and economic dynamics of the regions in which they operate (Sicily, Campania and Calabria, respectively), the *Sacra Corona Unita* can be considered a case of mafia's exploitation of a territory that was originally unaffected by mafia activity (Massari, 2014).

Several reasons explain mafia expansion in Apulia. First, the close proximity to Calabria and Campania, two Italian regions characterized by the presence of long-established mafia-type organizations, has played an important role (Pinotti, 2015).

Second, mafia expansion in Apulia can also be linked to historical phenomena. In the 1960s, with the end of the special economic status of the Moroccan port of Tangiers, the organized crime involved in tobacco smuggling abandoned the "Tyrrhenian route" (from Morocco to Marseilles, through Sicily and Naples) and redirected its interest towards the "Adriatic route". The eastern Apulian coast, and especially the city of Brindisi, became the natural destination of cigarette shipments from Albania and former Yugoslavia (see Pinotti, 2015 for further details).

Third, Apulia experienced a process of mafia diffusion through a forced resettlement program (*soggiorno obbligato*) which came into effect in 1956 and forced mafia bosses, either convicted or suspected, to exile in municipalities outside the mafia's traditional areas of operation. This program, originally aimed at cutting the links between mafia bosses and their networks, did in fact contribute to the infiltration of organized crime in the host municipalities. Between 1961 and 1972, Apulia was the region that hosted the largest number of criminals from other Southern Italian regions, most of them from Calabria, Campania, and Sicily (Pinotti, 2015). During the same period, according to the official reports of the Parliamentary Anti-Mafia Commission (PAC), Apulia also hosted a growing number of prison inmates belonging to the ranks of the *Nuova Camorra Organizzata*, who had been transferred from Campania to Apulia to avoid jail violence between opposing factions of the *Camorra*. Subsequent judiciary investigations revealed that this transfer actually contributed to making Apulia a breeding ground for organized crime (PAC, 1991; 1994).

The main contribution of our paper is to provide a quantitative assessment of the causal effect of mafia strength on soil consumption at the fine municipal level, taking advantage of a unique dataset that we constructed by merging several data sources. Although there is a smattering of literature on the effect of crime activities on the environment, paying particular attention to the problems of illegal waste management and waste traffic (see among others D'Amato et al., 2015; Di Pillo et al., 2023), and illegal building and land use (see among others Falco, 2017; Troisi, 2022), to our knowledge there is no paper that specifically studies the relationship between organized crime and soil consumption. Indeed, Colsaet et al. (2018), in their extensive review of scientific work addressing the determinants of land take, do not report any article investigating the relationship between soil consumption and crime. We attempt to fill this gap by considering two empirical strategies. One relies on a conditional independence assumption based on the availability of a rich set of controls at the municipality level. The other is an instrumental variables (IV) strategy that uses the forced resettlement program as a source of arguably exogenous variation in the presence of organized crime across municipalities.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 presents our empirical strategies. Results are discussed in Section 4. Finally, Section 5 summarizes and concludes.

2 Data

This paper is based on a unique dataset that we constructed by merging municipal-level information from a variety of sources. The main ones are the National System for Environmental Protection (SNPA) database for soil consumption, registry data from the National Fire and Rescue Service (*Corpo Nazionale dei Vigili del Fuoco*) for the strength of organized crime, registry data from the Provincial Police Headquarters of Bari (*Questura di Bari*) for the forced resettlement program, and the National Institute of Statistics (*Istituto Nazionale di Statistica* or Istat) population census and municipal databases for background variables. Our units of observation are Apulia's 258 municipalities, whose number and administrative borders have remained essentially unchanged over the past 70 years.

This section provides some detail on our two key variables, namely soil consumption and the strength of organized crime. Additional information on these two variables and the other variables employed in our analysis is contained in Section 3 and Appendix A.

2.1 Soil consumption

Our dependent variable is soil consumption, defined as the increase in artificial covering of originally non-artificial surfaces (namely, agricultural, forest, and other natural or semi-natural land) over a given time period as a result of anthropogenic activities (European Commission, 2007). This definition includes both permanently consumed soil (due to permanent artificial covering, such as buildings, paved roads, railway infrastructures, airports, ports, and other paved/impermeable areas) and reversibly consumed soil (due to reversible artificial covering, such as unpaved roads and other unpaved areas whose removal can restore the initial soil conditions). Since soil takes centuries or often millennia to develop, it is generally considered as a non-renewable resource, which justifies treating soil consumption as a non-negative variable.

For each Apulian municipality, we consider soil consumption between the years 2006 and 2018, measured in hectares per inhabitant and taken from the National System for Environmental Protection database maintained by the Italian National Institute for Environmental Protection and Research (*Istituto Superiore per la Protezione e la Ricerca Ambientale* or ISPRA) and the network of Environmental Protection Agencies of the Italian Regions and Autonomous Provinces.

Panel (a) of Figure 1 shows the distribution of soil consumption in the Apulian municipalities during the period considered. The intensity of the color increases with the level of soil consumption.

[Figure 1 about here]

We shall henceforth work with (average) annual soil consumption during the period 2006–2018.

2.2 Strength of organized crime

Our "treatment variable" is the strength of organized crime, a variable that is not easy to measure. Since organized crime acts illegally, and therefore tends to hide its activities, data are often lacking or, when available, represent an underestimate.

The literature has considered several measures of mafia strength. For example, Pinotti (2015) uses two of them: the number of cases ex Article 416-bis of the Italian Penal Code reported by the police to the judicial authority and the number of murders attributed to organized crime. Both measures are only available at the provincial level, not at the municipal level. Further, while the first is a sufficient but not necessary marker of mafia presence, the second has declined steadily since the early 1990s, a period characterized by a violent conflict between the Italian State and the Sicilian mafia. Over the last three decades, the number of mafia-related murders has fallen from 708 in 1991 to only 19 in 2020 (Istat, 2022). This trend underscores a shift away from the high levels of violence practiced by organized crime in the past, as modern mafias resort to intimidation through less sensational crimes like arson or extortion, while murders remain the last resort (Daniele, 2023).

We instead proxy the local strength of organized crime by the number of reported arsons in a municipality. Although other studies have used this variable (see for instance Caglayan et al., 2021; Daniele & Varani, 2011), we are the first to collect and use arson information at the fine municipality level. Arson is considered a "telltale crime" (*reato spia*) that marks the diffusion of mafias across a territory. Although not all instances of arson can be attributed to the intimidating activities of organized crime, in most cases this is the initial presumption of investigating authorities. Arson provides a strong signal, not only to the victims but also to the surrounding community, and can be considered a manifestation of territorial control through which criminals directly signal their presence and their weight (Mocetti & Rizzica, 2021).

The Italian Penal Code categorizes arson as a criminal offense, subject to a punishment ranging from three to seven years of imprisonment. According to the latest report from Italy's foremost non-profit environmental organization (Legambiente, 2023), the highest incidence of arson in 2021 was documented in Calabria, with 5.27 reports to the judicial police per 100,000 inhabitants, followed by Sicily (5.05), Sardinia (4.65), and Apulia (3.41). Notably, with the exception of Sardinia, the most affected regions are all in Southern Italy, where the presence of organized crime is more pronounced.

Arson exhibits a key feature: under-reporting is negligible because, when it occurs, it has to be extinguished by firefighters. The limited scope for under-reporting differentiates arson and murder from other crimes committed by mafias, such as drug or human trafficking, extortion, and fraud, for which under-reporting tends to be severe (Pinotti, 2015). Compared to murder, however, arson is not a last-resort tool, and its employment by organized crime has not declined in Italy over the last three decades (Istat, 2018).

In rural or forested areas, arson may also be carried out to facilitate changes in land use, typically to allow new construction to take place. As a result, illegal soil consumption may occur after an arson attack, independently of the presence of organized crime. This case has lost its relevance in Italy after the introduction in year 2000 of Law No. 353, aimed at defending the national forest heritage from fires. Specifically, Article 10 of this law prohibits any change in the intended use of forested areas or pastures damaged by fire for a period of fifteen years. The same law also prohibits any construction in these areas for a period of ten years, except for constructions that had already been planned by the existing urban planning instruments prior to the occurrence of the fire.

The information on the number of arsons was obtained from the registry of the National Fire and Rescue Service, and is only available for the period 2004–2014. Panel (b) of Figure 1 shows the distribution of the total number of arsons in the Apulian municipalities between 2004 and 2014. The intensity of the color increases with the number of arsons.

We shall henceforth work with the (average) annual number of arsons during the period 2004–2014.

A number of alternative measures of the local strength of organized crime will be discussed in Section 4.5.

3 Empirical strategies

Our goal is to estimate the effect of the strength of organized crime–the "treatment variable"–on soil consumption. We consider two empirical strategies: the first controls for observable confounding factors, while the second also allows for the presence of unobserved factors that cannot be controlled for directly.

3.1 Modeling the relationship between soil consumption and organized crime

Let C_i denote annual soil consumption in municipality $i = 1, \ldots, n$ during the period 2006–2018, with n the number of municipalities in our sample, and let A_i denote our proxy for the strength of organized crime, namely the annual number of arsons in municipality i during the period 2004–2014. We posit the existence of a scaling variable S_i (i.e., some measure of the "size" of the municipality) and smooth non-linear transformations g and h of the rescaled variables C_i/S_i and A_i/S_i such that, after applying these transformations, the conjectured causal relationship between the two variables is approximately linear; that is, we assume that

$$g(C_i/S_i) = \beta_0 + \beta_1 h(A_i/S_i) + \epsilon_i, \qquad i = 1, \ldots, n, \tag{1}$$

where β_0 and β_1 are unknown parameters and ϵ_i is an error term that captures the effect of all the other variables which influence soil consumption.

Figure 2 presents the empirical relationship between annual soil consumption and the annual number of arsons in our sample, both with and without transformation and rescaling. Panel (a) shows the scatterplot of the two variables without rescaling, panel (b) shows the scatterplot when both variables are transformed to (natural) logarithms, panel (c) shows the scatterplot of the two variables rescaled by the municipality's surface area, while panel (d) shows their scatterplot when both are rescaled and in logs. The figure illustrates how rescaling helps control for the different size of municipalities and how the log transformation helps reduce the impact of a few large outliers corresponding to the provincial capitals. This in turn suggests a simple log-log model for the relationship between the two variables, where the slope parameter β_1 has a natural interpretation as the elasticity of soil consumption with respect to the number of arsons.

[Figure 2 about here]

A difficulty with a log-log model for the relationship between soil consumption and arson is that it cannot be applied to municipalities with zero or missing values of either variable. Soil consumption between 2006 and 2018 is equal to zero for one Apulian municipality, is missing for two, and is always positive for the other 255 municipalities. As for arson, 25 Apulian municipalities record zero arsons between 2004 and 2014. These municipalities share the feature of being quite small: all of them have less than 6,000 inhabitants, and 23 have less than 3,000 inhabitants.[1] Since the absence of arsons during the period considered does not appear to be related to soil consumption and is almost entirely explained by the size of a municipality, we ignore selection issues and estimate a log-log model for the relationship between soil consumption and the number of arsons on a final sample of 231 municipalities with non-missing and non-zero values of the two variables. We shall consider two alternative strategies for estimating the elasticity β_1 from these data. The first, discussed in the next section, is an ordinary least squares (OLS) strategy based on the existence of a sufficiently rich set of controls to ensure that a conditional independence assumption holds. The second, discussed in Section 3.4, is an instrumental variables (IV) strategy based on the additional information provided by a plausibly valid instrument.

3.2 The conditional independence assumption and OLS

A simple log-log model for the relationship (1) is likely to omit other variables that affect soil consumption, i.e. are part of ϵ_i, and are correlated with the logarithm of the number of arsons. If some of these variables are observable (e.g., average income or socio-demographic characteristics of the municipality), they may be included on the right-hand side of model (1) as additional controls, that is, we may assume that the error term in (1) is of the form $\epsilon_i = \beta_3' X_i + e_i$, where β_3 is a vector of unknown coefficients, X_i is the vector of additional controls, and e_i is an error term whose properties are discussed below. This leads to an estimable relationship of the form

$$c_i = \beta_0 + \beta_1 a_i + \beta_2 s_i + \beta_3' X_i + e_i, \qquad i = 1, \ldots, n, \tag{2}$$

where c_i is the logarithm of annual soil consumption during the period 2006–2018, a_i is the logarithm of the annual number of arsons during the period 2004–2014, and s_i is the logarithm

[1] Shortening the observation period leads to an increase in the number of municipalities exhibiting zero arsons. This supports the hypothesis that arsons are rare events, especially in small municipalities.

of the scaling variable. The parameter of interest is the elasticity β_1, while all the other coefficients are treated as "nuisance" parameters.

A useful interpretation of model (2) is the following. Suppose that artificial land covering L_{it} in municipality i evolves through time according to a flexible model of the form $L_{it} = \mu_i + \psi_{it} t$, where the intercept μ_i captures time-invariant unobserved characteristics of the municipality, ψ_{it} is the slope of a municipality-specific time-varying trend that may depend on both observable and unobservable variables, and t is calendar time. Since soil consumption between $t-1$ and t is equal to $C_{it} = L_{it} - L_{i,t-1} = (\psi_{it} - \psi_{i,t-1})t + \psi_{i,t-1}$, considering this particular outcome effectively removes the unobserved municipality-specific effect μ_i, which greatly simplifies our problem by eliminating an important source of endogeneity. Further, under the assumption that the trend slope varies little over time, $C_{it} \approx C_{i,t-1}$. Because soil consumption can be represented as a non-negative continuous random variable, a natural model for $\psi_{i,t-1}$ is the log-linear specification $\psi_{i,t-1} = \exp(\beta_0 + \beta_1 a_{i,t-1} + \beta_2 s_i + \beta_3' X_{i,t-1} + e_{i,t-1})$, where $X_{i,t-1}$ is a vector of observable municipal characteristics and $e_{i,t-1}$ is an unobservable time-varying random component. In turn, this specification implies that $c_{it} = \ln(C_{it}) + \beta_0 + \beta_1 a_{i,t-1} + \beta_2 s_i + \beta_3' X_{i,t-1} + e_{i,t-1}$. Taking time averages, denoted by avg, gives model (2) with $a_i = \text{avg}(a_{i,t-1})$, $X_i = \text{avg}(X_{i,t-1})$, and $e_i = \text{avg}(e_{i,t-1})$.

The interpretation and estimation of the elasticity β_1 crucially depend on the assumptions one is willing to make about the relationship between a_i, s_i, X_i, and e_i. If one can credibly assume that a_i is uncorrelated with e_i after controlling for s_i and the variables in X_i, then β_1 can be taken to measure the causal effect of criminal activity (proxied by the number of arsons) on soil consumption and can be estimated consistently by an ordinary least squares (OLS) regression of c_i on a constant term, a_i, s_i, and X_i.

3.3 Choice of control variables

The validity of the OLS strategy in the previous section relies on an appropriate choice of the control variables to include in X_i. The existing literature has identified a number of potential predictors of soil consumption, such as the territorial characteristics of a locality, its demographic structure, and socio-economic indicators (see for example Plieninger et al., 2016), though there is considerable uncertainty about their relative importance. Further, these predictors are only defined in broad terms, so there is additional uncertainty about their precise definition.

As for the territorial characteristics of a municipality, we always control for whether it is a provincial capital and whether it is located along the coast. Specifically, we always include among the controls a binary indicator with value 1 if the municipality is a provincial capital and value 0 otherwise. The term "province" in Italy refers to a second-level administrative division–an intermediate level between regions and municipalities–and the provincial capitals are the municipalities that are the administrative centers of a province.[2] We include this binary indicator as a control in order to account for the peculiar situation of these municipalities, which tend to present a higher concentration of economic and administrative activities that may lead to extra demand of soil compared to the other municipalities. In addition, provincial capitals were not directly affected by the presence of resettled bosses, who were predominantly sent to municipalities that were only a few kilometers away (PAC, 1978).

The "mandatory controls" also include a binary indicator with value 1 if the municipality borders the sea coast and value 0 otherwise. In the last decades, because of the residential development for second and holiday homes and the development of the tourism industry along the sea coast, the Italian coastal areas have been subject to intense anthropogenic pressure and urbanization processes, which have strongly affected land use and soil consumption in coastal municipalities and permanently scarred the natural and urban landscape (Falco, 2017).

Demography is increasingly recognized as a key determinant of land use: the population structure and dynamics may affect housing demand, individual preferences for alternative living arrangements, demand for services, etc. In turn, this may affect the patterns of landscape development in a municipality, and, consequently, the level of soil consumption (Plieninger et al., 2016). Hence we include population growth and indicators for the population age structure as "auxiliary controls", for which we are less certain. Population growth is measured over the 10-year period between 2001 and 2011, while the indicators for the age structure of the population are the ratio of the number of people aged 65 years or more (65+) to the number of people aged 0–14 years, or "aging index", and the fraction of children aged 0–5 years.

Variations in land use and soil consumption could also be the result of differences in the socio-economic context across municipalities, thereby reflecting not only differences in average incomes, but also differences in the educational attainments of the population, local labor

[2] Although Apulia is currently divided into six provinces, named after their provincial capitals of Bari, Barletta-Andria-Trani, Brindisi, Foggia, Lecce, and Taranto, we do not treat the municipalities of Barletta, Andria and Trani as provincial capitals because, when the forced resettlement program started in year 1956, Apulia was divided into only five provinces, namely Bari, Brindisi, Foggia, Lecce, and Taranto.

market conditions, and the composition of the workforce by industry or occupation of employment (Liu et al., 2013). Thus, as auxiliary controls, we also consider the municipal GDP per employee and a set of indicators for the educational attainments of the population (the fraction of residents aged 15–19 years with a lower or upper secondary degree, the fraction of residents aged 30–34 years with university degree, the holders of a high school diploma or bachelor's degree divided by the total number of residents aged 6 years and older, and the illiterates, literates without qualifications and holders of a primary school diploma divided by the total number of residents aged 6 years and older), local labor market conditions (rates of unemployment, youth unemployment and youth employment), and the composition of the municipal workforce by industry or occupation of employment (employment in construction, employment in manufacturing, employment in the services, employment in non-retail services, and self-employment).

Table A.1 of the Appendix presents the definition of all our control variables (mandatory and auxiliary). As for the sources of information, the territorial characteristics of a municipality are taken from the Italian National Institute of Statistics (Istat) Municipality Database, the demographic and socioeconomic indicators are taken from the Istat Population Census Database with reference to the year 2001, while the municipal GDP per employee in 2001 is taken from the report produced by *Rete Urbana delle Rappresentanze* (RUR, 2004), an Italian center for economic and territorial analysis.

3.4 Relaxing the conditional independence assumption

There are reasons to believe that, even after controlling for a scaling variable and a sufficiently rich set of controls, our "focus regressor" a_i is endogenous (i.e. correlated with e_i), in which case the coefficient β_1 cannot be interpreted as the causal effect of mafia's criminal activity on soil consumption and cannot be estimated consistently by an OLS regression of c_i on a constant term, a_i, s_i, and X_i.

First, the number of arsons is likely to be an imperfect proxy for the local strength of organized crime. This errors-in-variables issue creates an endogeneity problem, as it results in correlation between the logarithm of the number of arsons and the structural error e_i that complicates the task of identifying the causal relationship of interest.

Second, an endogeneity problem could also arise because the set of controls included in X_i may omit variables which are difficult to observe or measure but affect soil consumption and are correlated with the number of arsons. For example, municipalities with high levels of soil consumption are likely to also exhibit poor administrative and managerial skills, or low independence of local politicians and administrators from the economic interests of criminal organizations. These variables are known to be associated with the territorial spread of organized crime (Abello-Colak & Guarneros-Meza, 2014), but are hard to control for.

To address these two endogeneity problems at the same time, we adopt an IV strategy by specifying a "triangular" system that consists of two regression equations. The first equation is the "structural" regression (2), where a_i is now assumed to be correlated with e_i even after controlling for s_i and X_i, while the second is the "first-stage" regression

$$a_i = \gamma_0 + \gamma_1 z_i + \gamma_2 s_i + \gamma_3' X_i + u_i, \qquad i = 1, \ldots, n, \tag{3}$$

where z_i is our candidate instrument, the γ's are unknown parameters, and u_i is an error term potentially correlated with the error term in (2). Our parameters of interest in this equation system are the elasticity β_1 in (2) and the semi-elasticity γ_1 in (3), with all the other parameters treated as nuisance parameters. Substituting the first-stage regression (3) into the structural regression (2) gives the "reduced-form" regression

$$c_i = \delta_0 + \delta_1 z_i + \delta_2 s_i + \delta_3' X_i + v_i, \qquad i = 1, \ldots, n, \tag{4}$$

where $\delta_0 = \beta_0 + \beta_1 \gamma_0$, $\delta_j = \beta_1 \gamma_j$ for $j = 1, 2, 3$, and $v_i = \beta_1 u_i + e_i$. If β_1 and γ_1 have the same sign (e.g., both are positive, as we expect) then $\delta_1 > 0$, while if either β_1 or δ_1 are zero then $\delta_1 = 0$. Further, $\beta_1 = \delta_1/\gamma_1$ whenever $\gamma_1 \neq 0$.

The first-stage regression (3) and the reduced-form regression (4) offer valuable information about the validity of the proposed instrument (Angrist & Lavy, 1999, Chernozhukov & Hansen, 2008). For example, finding that $\delta_1 = 0$ reveals that $\beta_1 = 0$.

The elasticity β_1 can be identified and consistently estimated if z_i is a valid instrument, that is, if it is both exogenous (i.e., uncorrelated with e_i) and relevant (i.e., "sufficiently correlated" with a_i). With a single endogenous regressor and a single instrument, our model is "just identified" and the simple IV estimator of β_1 coincides with the well known two-stage least squares (2SLS) estimator.

3.5 Identification strategy

Our identification strategy exploits the variation in the number of arsons across municipalities induced by the forced resettlement program (*soggiorno obbligato*) described in the Introduction, which arguably acted as an exogenous positive shock for the territorial spread of organized crime in Apulia. The program was established by Law No. 1423/1956. Its rationale was to isolate and control particularly dangerous individuals, such as suspected members of organized crime. Subsequently, Law No. 575/1965 facilitated the application of the program to mafia cases and harshened the punishment for those who failed to comply. Nevertheless, the problem of an effective police control of the "soggiornanti" persisted. Law No. 646/1982 tried to address the issue by stiffening the punishment for the violators and restricting the resettlement to municipalities sufficiently far from major towns and with no more than 5,000 inhabitants. Law No. 1423/1956 and its various modifications were finally abolished with the referendum of July 11, 1995.

Figure 3 shows the distribution of the number of forced resettlements in the Apulian municipalities during the period 1956–1995. The information is taken from the registry data maintained by the Provincial Police Headquarters of Bari (*Questura di Bari*). The number of forced resettlments ranges between a minimum of zero and a maximum of five. If we confine our attention to the 231 municipalities in our sample: 127 of them have no forced resettlement (including the 5 provincial capitals), 52 have only one, 30 have two, 12 have three, 4 have four, and only one has 5.

[Figure 3 about here]

Our proposed instrument is a binary indicator with value 1 if a municipality hosted one or more mafia bosses during the period 1956–1995, and value 0 otherwise. This identification strategy relies on the assumption that the forced resettlement of mafia bosses in Apulia, well outside their traditional areas of influence, can be regarded as an exogenous determinant of the spread of organized crime; this, in turn, affects soil consumption through its effect on the local strength of organized crime, as proxied by the logarithm of the number of arsons in the municipality.

To be a valid instrument, our indicator of forced resettlement must satisfy two conditions. First, its correlation with the logarithm of the annual number of arsons must be sufficiently strong. Second, it must be uncorrelated with the error term. We test the first assumption by a standard F-test for the significance of the instrument in the first-stage equation (3). Although it is not possible to test whether the second condition is met (as the structural error e_i is unobserved), Section 4.4 presents some evidence to support its validity. If these two key assumptions are satisfied, and our log-log model (2) is correctly specified, then the 2SLS estimate of the parameter β_1 is consistent for the effect of organized crime on soil consumption.

Although a just-identified IV estimator has a standard asymptotically normal distribution under random sampling from a well-defined infinite population, its finite-sample distribution is far from normal and does not have moments of any order. In particular, its mean and variance do not exist.[3] Angrist and Kolesár (2023) point out that, even in this case, usual inference strategies are reliable provided the degree of endogeneity is not too large and the instrument is sufficiently strong, as measured in our case by the square of the t-statistic on the semi-elasticity γ_1 in the first-stage equation (3).[4]

4 Empirical results

After presenting some descriptive statistics in Section 4.1, we discuss our OLS and IV estimates of the structural equation (2) in Section 4.3 and the estimates of the first-stage equation (3) and the reduced-form equation (4) in Section 4.4.

4.1 Descriptive statistics

Table 1 presents sample means and standard deviations for all the variables we use. Our sample is limited to the 231 Apulian municipalities with non-zero values of soil consumption and arsons and no missing values on other key controls. The sample average of the annual number of arsons over the period 2004–2014 is 3.34, that of annual soil consumption over the period 2006–2018 is about 35 hectares, while only 43% of the municipalities in our sample were affected by the forced resettlement program. Apulian municipalities tend to have lower levels of human capital, higher unemployment rates, and lower incomes relative to the Italian

[3] Since our sample consists of all Apulian municipalities, it is not clear what population our sample comes from. Justifying the use of conventional statistical inference in this and similar settings (e.g., when regions or countries are the units of observation), as we do, requires the implicit reliance on the somewhat contentious assumption of random sampling from a super-population.

[4] Angrist and Kolesár (2023) provide a nice characterization of actual rejection rates of conventional t-tests in a single-variable just-identified normal (Gaussian) IV model. They show that the asymptotic results provide a good approximation except when (i) endogeneity (measured, under homoskedasticity, by the correlation between the structural errors e_i and the first-stage errors u_i) is very high, and (ii) the instrument is very weak (i.e., the value of the squared population first-stage t-statistic on the instrument z_i is close to 1), which is definitely not our case (see Section 4.4). This result follows from the fact that while the (median) bias of the IV estimator rises as the instrument grows weaker, its standard error also increases. This contrasts with the results for over-identified 2SLS with many weak instruments, where the usual 2SLS standard errors remain small enough for t-tests to be misleading.

average. For example, based on the 2001 population census, the percentage of individuals aged 30–34 with a university degree is about 10% on average across our municipalities against a national percentage of 12.9% (Eurostat, 2001), while the average unemployment rate stands at 20% against a national unemployment rate of about 9.5% (Istat, 2001). As to GDP per capita in 2001, the value for the Apulia region was EUR 16,981 against EUR 22,882 for Italy as a whole.[5]

[Table 1 about here]

4.2 Assignment of municipalities to the forced resettlement program

To test whether the assignment of municipalities to the the forced resettlement program may be regarded as approximately random, we regress the binary indicator of forced resettlement using a standard logit model that includes as covariates a set of demographic and socio-economic municipal characteristics computed from the 1951 Population Census data, thus avoiding reverse causality issues. We exclude provincial capitals from the sample because the law prevented them from hosting resettled bosses. Table B.1 of the Appendix shows that, although a couple of covariate are weakly statistically significant (e.g., the fraction of people with a high-school or bachelor degree in specification L3 and the aging index in specifications L2 and L6), no set of covariates considered is jointly statistically significant, implying that we cannot predict participation in the forced resettlement program based on the available characteristics of a municipality.

We also carry out a "balancing test" that compares the means of all relevant pre-program covariates across municipalities "treated" and "untreated" under the forced resettlement program. The results, presented in Table B.2 of the Appendix, show no systematic mean differences between the two groups, except possibly for the fraction of people with a high-school or bachelor degree and the aging index.

4.3 Estimates of the structural equation

Tables 2 and 3 present, respectively, OLS and IV estimates of the elasticity β_1 for seven different specifications of the structural equation (2), which differ from each other by the number and

[5] GDP at current market price by NUTS 2 regions is available from Eurostat at https://ec.europa.eu/eurostat/databrowser/bookmark/46b2f068-c4fd-4395-92cd-ad14fbbe2ac4?lang=en.

type of included controls. They also present heteroskedasticity-robust standard errors and 95% (asymptotic) confidence intervals for β_1.[6]

In addition to the logarithm of the number of arsons, the specification in the first column of each table (LS1 or IV1) only includes a constant term and indicators for provincial capital and coastal municipality, while the other six specifications add the logarithm of a scaling variable (the municipal surface area or the population density) and explore the sensitivity of the estimates of β_1 to the inclusion of alternative sets of auxiliary controls from the five different domains discussed in Section 3.3 (demographics, schooling attainments, labor market conditions, employment structure by industry or occupation, and income). From the $3 \times 2^{16} = 196,608$ estimated models (namely, $2^{16} = 65,536$ for each of the three scaling variables), we report the results for six that present large IV estimates of β_1, non-overlapping OLS and IV confidence intervals for β_1, and large values of the first-stage F-test statistic on γ_1. We are not interested in the coefficients on the controls, as they do not generally have a causal interpretation, so we only list which controls are included in each specification. Point estimates, standard errors and confidence intervals for these coefficients are available from the Authors upon request.

Table 2 presents the OLS estimates of β_1. These estimates, which ignore endogeneity issues, suggest that the presence of organized crime has a positive and statistically significant association with soil consumption. The estimated elasticities are always less than one and, excluding the first specification (LS1), range from a minimum of .530 with a 95% confidence interval of [.437, .624] for the third specification (LS3) to a maximum of .619 with a 95% confidence interval of [.540, .700] for the first specification (LS1). On average across models, the OLS estimates of β_1 are about .60, meaning that a 10% increase in the strength of organized crime, as measured by the number of arsons, is associated with a 6% increase in annual soil consumption.

[Table 2 about here]

Table 3 presents the corresponding IV estimates of β_1 using as instrument the binary

[6] Given the limited sample size ($n = 231$ observations), our estimated standard errors incorporate an adjustment for the degrees of freedom which, with $k = 11$ regression parameters, inflates the standard errors by a factor of $\sqrt{n/(n-k)} = \sqrt{231/220} = 1.025$ with respect to the unadjusted estimates. Our confidence intervals also use the quantiles of the t-distribution with $n - k$ degrees of freedom rather than those of the standard normal. As a result, our confidence intervals are larger and therefore more conservative than the usual ones based on the asymptotically normal approximation.

indicator of forced resettlement. These IV estimates are always greater then one and are statistically significant at the 5% level–except in the second specification (IV2), where they are statistically significant only at the 10% level. If we ignore this specification, they range from a minimum of 1.166 with a 95% confidence interval of [.645, 1.686] for the sixth specification (IV6) to a maximum of 1.239 with a 95% confidence interval of [.597, 1.880] for the first specification (IV1). On average across models, the IV estimates of β_1 are about 1.20, meaning that a 10% increase in the strength of organized crime, as measured by the number of arsons, is associated with a 12% increase in annual soil consumption. Further, except for the first two specifications, the IV and LS confidence intervals never overlap despite IV having larger standard errors than LS. These results indicate that an increased presence of organized crime causes not just an increase, but a more than proportional increase in soil consumption.

[Table 3 about here]

A number of reasons, not mutually exclusive, may explain why our IV estimates are always much larger than the corresponding OLS estimates. The first reason is that the number of arsons is a noisy measurement of the local strength of organized crime (the true "signal") so, under a classical measurement error process where the signal and the noise are uncorrelated, the OLS estimates are downward biased for β_1. Since the IV estimates are about twice as large as the OLS estimates, the classical formula for the attenuation bias of OLS would then imply that the signal and the noise have about the same variance.[7]

The second reason is the downward bias of the OLS estimates due to the omission from X_i of variables that are correlated with both soil consumption and the number of arsons, the two correlations having opposite sign. One such variable is the amount of money that a mafia clan extracts from the territory under its control, and is actually laundered or used for corruption in a specific municipality within that territory. This variable may affect soil consumption and the number of arsons in opposite ways, thus leading to a positive difference between the IV and the OLS estimates. On the one hand, given the crucial role of the construction industry in money laundering, extracting and recycling larger amounts of cash may lead to more construction activity and therefore more soil consumption. On the other hand, a negative correlation

[7] From the classical attenuation bias formula, the probability limit of the OLS estimator of β_1 is equal to $\beta_{1,LS} = \beta_1\sigma_*^2/(\sigma_*^2 + \sigma_\eta^2)$, where σ_*^2 is the variance of the signal (the extent of the presence of organized crime) across municipalities, and σ_η^2 is the variance of the noise. If our IV estimator is consistent for β_1, then our results imply that thr ratio of the probability limits of the OLS and IV estimators is equal to $\beta_{1,LS}/\beta_{1,IV} = \sigma_*^2/(\sigma_*^2 + \sigma_\eta^2) \approx 1/2$ and therefore that $\sigma_*^2 \approx \sigma_\eta^2$.

between the number of arsons and the amount of cash locally available to the mafia may result from its efficient use of two opposite instruments: bribes and arson. As pointed out by Dal Bó et al. (2006), a decrease in the cost of bribes makes them more attractive, resulting in a substitution of threats with bribes. Since the availability of large amounts of cash extracted by a mafia clan in the territory under its control is likely to decrease the cost of bribes, this would reduce the need of relying on arson to "mollify" the intended targets. Another variable that has been omitted, for both conceptual and practical reasons, is the degree of independence or moral integrity of local politicians and public administrators. Unlike the cash example, this variable is likely to negatively affect soil consumption but positively affect the number of arsons. Indeed, a lower degree of independence or moral integrity of local politicians and administrators makes it easier for the mafia to obtain building permits or changes in the use of land in exchange for electoral support (De Feo & De Luca, 2017), resulting in more soil consumption. At the same time, an increased presence of upstanding local politicians and administrators may increase the number of arsons targeting them, as the mafia resorts to this instrument in an attempt to achieve its goals.

A third reason is variation in the model parameters across municipalities. If the elasticity β_1 in the structural equation (2) varies across municipalities and is positively correlated with the semi-elasticity γ_1 in the first-stage equation (3), then our IV approach may not estimate the average value of the elasticity of soil consumption across municipalities but a local average treatment effect (Angrist & Imbens, 1995), namely a particular weighted average of the heterogeneous elasticities in the different municipalities that gives more weight to those municipalities where the forced resettlement program had a greater impact on the diffusion of organized crime. The LATE parameter is necessarily greater, and can be much greater, than the average value of the elasticity of soil consumption. Further, its magnitude depends on the particular instrument considered and may change if a different instrument is employed.

4.4 Estimates of the first-stage and reduced-form regressions

Table 4 presents the estimates of γ_1 in the first-stage regression (3) for the seven specifications discussed in the previous section, along with their standard errors and 95% confidence intervals. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request.

The estimates for the specifications with the population density as the scaling variable

(FS3–FS7) show that the "treated" municipalities, i.e. those subject to the forced resettlement program, experience an increase in the number of arsons of almost 50% relative to the "untreated" municipalities. The estimated coefficient on the forced resettlement indicator varies little across these five specifications, is always strongly statistically significant, and the "first-stage F-statistic" (the square of the t-statistic on γ_1) ranges from a minimum of 12.3 for fourth specification (FS4) to a maximum of 13.6 for the sixth specification (FS6), always exceeding the threshold of 10 typically employed to detect weak instruments (see, e.g., Stock et al., 2002).

[Table 4 about here]

Table 5 presents the estimates of δ_1 in the reduced-form regression (4) for the seven specifications presented in the previous section, along with their standard errors and 95% confidence intervals. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request.

The estimates for the specifications with the population density as the scaling variable (RF3–RF7) show that the "treated" municipalities experience an increase in soil consumption of nearly 60% relative to the "untreated" municipalities. The estimated coefficient on the forced resettlement indicator varies little across these five specifications and is always strongly statistically significant.

[Table 5 about here]

4.5 Alternative measures of mafia strength

To check the robustness of our results, we also consider the information from four additional measures of the strength of organized crime in the Apulian municipalities.

The first consists of the number of cases of intimidation and threat – different from arson – against local public administrators during the period from 2008 (the year these data were first released) to 2014, obtained from *Avviso Pubblico–Enti Locali e Regioni Contro Mafie e Corruzione*, an association promoting transparency and integrity in public administrations. The second is the number of real estate properties seized from mafia affiliates during the period 1998—2014,[8] obtained from *Agenzia Nazionale per l'Amministrazione e la Destinazione*

[8] Italian Law 109/1996 establishes that assets confiscated from mafias by the State can be reused for social purposes. Almost 80 percent of the number of confiscated real estate has been destined to municipalities that can directly administer the properties or assign them as a free concession to non-profit organizations.

dei Beni Sequestrati e Confiscati alla Criminalità Organizzata, the national public agency in charge of the program. The third is a census of mafia clans operating in a municipality in 2014, obtained from the Anti-Mafia Investigative Directorate (*Direzione Investigativa Antimafia*). The fourth is the number of innocent mafia victims from 1974 to 2014, obtained from the network *Libera–Associazioni, Nomi e Numeri Contro le Mafie*. These four measures are described in more detail in Appendix A.3.

Following Caglayan et al. (2021), we employ factor analysis to combine these four measures into a single index of mafia strength that we then use as an alternative to the number of arsons.[9] Tables 6 and 7 respectively present the OLS and IV estimates of β_1 using this alternative index. These estimates are very similar to those in Tables 2 and 3.[10] In particular, they are always positive and are highly statistically significant in all specifications except the second. They are also close in value to those obtained using the number of arsons as a measure of the local strength of organized crime, namely positive but below one for OLS and above one for IV. Further, except for the first two specifications, the IV and LS confidence intervals never overlap despite IV having larger standard errors than LS, thus confirming all our previous results.

[Table 6 about here]

[Table 7 about here]

Finally, Table 8 presents estimates of γ_1 in the first-stage regression (3) using the log of our mafia index to proxy the mafia strength. As with the LS and IV estimates, using this alternative measure provides similar results supporting the robustness of our analysis.

[Table 8 about here]

[9] To construct this index, we first tested for appropriateness of factor analysis computing the determinant of the matrix correlation and performing both the Bartlett's test for sphericity and the Kaiser-Mayer-Olkin measure of sampling adequacy. We then computed the underlying factors using the method of principal factors and retained two factors. Finally, we carried out an orthogonal varimax rotation of the loading matrix.

[10] The value of the mafia index is positive for all 255 Apulian municipalities, so it is always possible to take its logarithm. However, for comparability reasons, we present results for the same sample of 231 municipalities used in Tables 2 and 3. The results for the sample of 255 municipalities, available upon request, are qualitatively the same.

4.6 Discussion

Mafia bosses, local politicians and entrepreneurs are very skilled at making collusive relationships also in expansion territories (see for example Varese, 2011 and Dagnes et al., 2020). These relationships are essential means for mafia-type organizations to infiltrate the legal economy, and ample judicial evidence signals that mafias mostly invest in the construction sector. Reports by *Avviso Pubblico* also reveal that mafias resort to threat and intimidation to subjugate public administrators involved with building licences and permits, urban planning, protection of the environment, public works, etc. – all sectors strictly related to soil consumption. In this respect, Le Moglie & Sorrenti (2022) show that, after the 2007 financial crisis, Italian provinces highly affected by the mafias presence experienced a less-severe drop in the number of new construction firms than the other provinces. In the construction industry, the possibility of laundering large amounts of cash with ease, either during the building activities or subsequently, through the investment opportunities generated in the real estate market, makes this sector particularly attractive for organized crime.

The construction industry is very appealing to mafia also for other reasons. One is its tight link with the system of local public procurement. Indeed, through exchange of favors, bribes and if necessary threats and violence–the latter highly perceived by the local community–mafias can affect awarding of public contracts and foster lenient treatment from inspection and regulatory bodies to entrepreneurs close to the mafias who neglect ecological planning and "green" norms. Another is the mafia's ability to increase the market concentration in this industry to its advantage (Ferrante et al., 2021) and then govern a network that goes from input and production to sale. Finally, the technological level generally low in this sector that allows hiring low-skilled labor useful to favor mafia strength in the community and control of territory. We argue that the causal effect of mafia on soil consumption shown in our results works through both the collusive relationships between mafia and local politicians, and the infiltration and rooting of mafia in the construction industry driven by the opportunities it offers to launder money.

5 Conclusions

Our paper contributes to both the literature on environmental issues and the literature on the economic consequences of mafias. To the best of our knowledge, it is the first to investigate illicit drivers of land-use change and soil consumption. Using data from the Southern Italian region of Apulia – a case of mafia transplantation, not unlike other cases in Central and Northern Italy during the same period – it quantifies the causal effect that the expansion of organized crime has on soil consumption. It shows that the spread of organized crime has a positive and statistically significant effect on soil consumption, with the elasticity of soil consumption to the number of arsons estimated to be below one for OLS but above one for IV.

Some policy implications of our work are worth mentioning. Artificial land development implies soil consumption, the most intense form of land acquisition for its consequences on reduced carbon sequestration, flooding, etc. Since the seminal paper by Nordhaus (1977), there has been an intense debate on carbon emission policies to combat global warming. Two competing approaches are "cost-imposing policies", which impose a cost on carbon, and "cost-reducing policies", which instead seek to reduce the cost of shifting to less carbon-intensive processes (Clausing & Wolfram, 2023). In the spirit of the former, carbon emissions could also be limited by curbing artificial land development, especially that connected to criminal activities and money laundering.

More generally, environmental crimes generate substantial profits for criminal organizations but are hard to detect and difficult to prosecute, making them particularly attractive to mafia-type organizations. It is therefore crucial to strengthen current environmental protection regulations and to take actions to combat criminal networks involved in all forms of environmental crimes.

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Table 1: Descriptive statistics.

Variable	Mean	Std. dev.
Annual number of arsons	3.34	7.78
Annual soil consumption	2.908	4.72
Forced resettlement	.429	.496
Innocent victims of mafias	.338	1.25
Mafia clans	.567	1.53
No-arson threats & intimidations to public administrators	.364	.927
Seized real estate from mafias	7.095	18.0
Activity Index	.382	.051
Aged 15–19 with secondary degree	.968	1.84
Aged 30–34 with university degree	.099	3.48
Aging index	1.10	39.6
Children aged 0–5	.060	.960
Coastal municipality	.273	.446
Empl. in construction	.134	.037
Empl. in manufacturing	.196	.061
Empl. in non-retail services	.390	.082
Empl. in services	.522	.091
GDP per employee	24.2	10.5
High education	.258	.048
Low education	.438	.042
Population change 2001–2011	151.7	1127.8
Population density	289.0	278.3
Population size (1000s)	17.3	29.8
Provincial capital	.022	.146
Self-employed	.259	.056
Surface area	81.1	94.3
Unemployment	.200	.044
Youth empl. 15–29	.291	4.58
Youth unemployment	.463	9.13
# observations	231	

Notes: All variables are presented as fractions except soil consumption (hectares), arson (number of arsons), surface area (square kilometers) and population change (number of residents).

Table 2: OLS regressions of the logarithm of annual soil consumption on the logarithm of the annual number of arsons.

Covariate	LS1	LS2	LS3	LS4	LS5	LS6	LS7
Log arsons	.619	.534	.530	.531	.531	.533	.545
	(.041)	(.060)	(.047)	(.048)	(.049)	(.048)	(.049)
	[.540, .700]	[.416, .651]	[.437, .624]	[.437, .624]	[.435, .628]	[.438, .628]	[.449, .642]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11
R^2	.601	.661	.630	.630	.630	.630	.645
Adjusted R^2	.595	.648	.618	.616	.616	.615	.628

Notes: The table presents the OLS estimates of β_1 in model (2) for a variety of specifications, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

Table 3: IV regressions of the logarithm of annual soil consumption on the logarithm of the annual number of arsons, with the binary indicator of forced resettlement as an instrument.

Covariate	IV1	IV2	IV3	IV4	IV5	IV6	IV7
Log arsons	1.239 (.326) [.597, 1.880]	1.145 (.660) [-.155, 2.445]	1.169 (.267) [.642, 1.696]	1.190 (.277) [.645, 1.735]	1.199 (.280) [.646, 1.751]	1.166 (.264) [.645, 1.686]	1.179 (.267) [.654, 1.705]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11

Notes: The table presents the IV estimates of β_1 in model (2) for the seven specifications presented in Table 2, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

Table 4: First-stage regressions of the logarithm of the annual number of arsons on the binary indicator of forced resettlement and alternative sets of controls.

Covariate	FS1	FS2	FS3	FS4	FS5	FS6	FS7
Forced resettlement	.457	.201	.506	.492	.486	.507	.494
	(.173)	(.140)	(.142)	(.141)	(.138)	(.139)	(.137)
	[.116, .799]	[-.076, .478]	[.226, .786]	[.215, .769]	[.215, .757]	[.233, .781]	[.224, .764]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11
R^2	.201	.544	.472	.479	.498	.484	.506
Adjusted R^2	.190	.528	.456	.460	.480	.463	.483
First-stage F-statistic	6.97	2.05	12.70	12.27	12.51	13.33	13.03

Notes: The table presents the OLS estimates of γ_1 in model (3) for the seven specifications presented in Table 2, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

Table 5: Reduced-form regressions of the logarithm of annual soil consumption on the binary indicator of forced resettlement and alternative sets of controls.

Covariate	RF1	RF2	RF3	RF4	RF5	RF6	RF7
Forced resettlement	.567	.230	.592	.586	.583	.591	.583
	(.144)	(.130)	(.119)	(.118)	(.117)	(.119)	(.116)
	[.284, .849]	[-.026, .487]	[.357, .827]	[.352, .819]	[.353, .813]	[.357, .825]	[.355, .811]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11
R^2	.209	.483	.468	.469	.477	.470	.483
Adjusted R^2	.199	.465	.451	.450	.458	.449	.459

Notes: The table presents the OLS estimates of δ_1 in model (4) for the seven specifications presented in Table 2, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

Table 6: OLS regressions of the logarithm of annual soil consumption on the logarithm of the mafia index.

Covariate	LS1	LS2	LS3	LS4	LS5	LS6	LS7
Log mafia index	.404	.263	.300	.299	.294	.303	.312
	(.042)	(.043)	(.042)	(.042)	(.042)	(.042)	(.043)
	[.321, .487]	[.178, .347]	[.217, .383]	[.216, .382]	[.211, .377]	[.220, .387]	[.227, .398]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11
R^2	.387	.549	.517	.519	.519	.52	.531
Adjusted R^2	.379	.532	.502	.502	.502	.5	.51

Notes: The table presents the OLS estimates of β_1 in model (2) for a variety of specifications, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

Table 7: IV regressions of the logarithm of annual soil consumption on the logarithm of the mafia index, with the binary indicator of forced resettlement as an instrument.

Covariate	IV1	IV2	IV3	IV4	IV5	IV6	IV7
Log mafia index	1.151	.793	1.07	1.06	1.08	1.02	1.15
	(.392)	(.545)	(.323)	(.325)	(.336)	(.299)	(.360)
	[.380, 1.923]	[-.282, 1.867]	[.431, 1.705]	[.420, 1.701]	[.422, 1.746]	[.430, 1.606]	[.442, 1.859]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11

Notes: The table presents the IV estimates of β_1 in model (2) for the seven specifications presented in Table 2, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

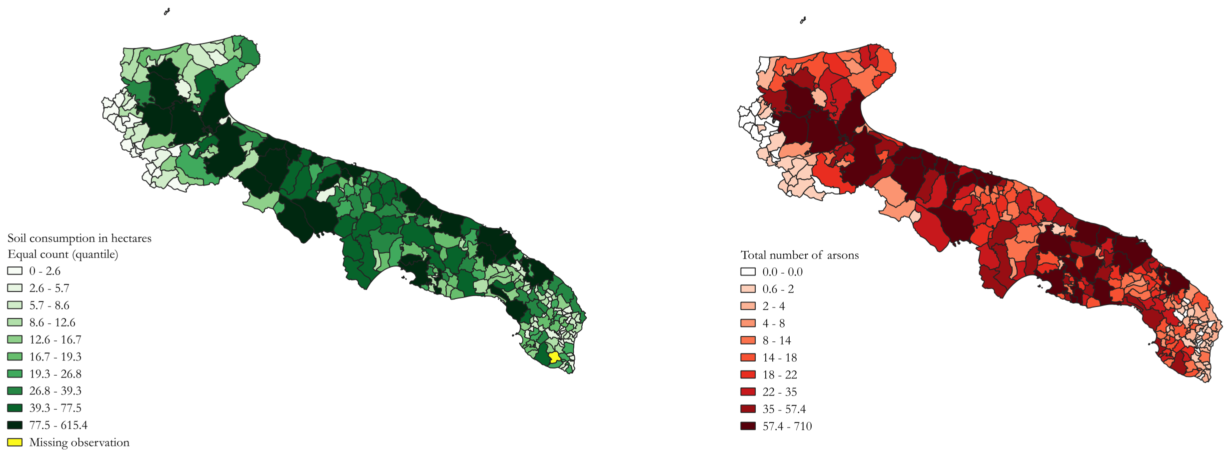
Table 8: First-stage regressions of the logarithm of the mafia index on the binary indicator of forced resettlement and alternative sets of controls.

Covariate	FS1	FS2	FS3	FS4	FS5	FS6	FS7
Forced resettlement	.492	.290	.554	.552	.538	.581	.506
	(.190)	(.193)	(.175)	(.175)	(.169)	(.172)	(.165)
	[.117, .867]	[-.090, .671]	[.208, .900]	[.208, .897]	[.204, .872]	[.241, .921]	[.180, .832]
Aged 15–19 with secondary degree		x					
Aging index			x	x	x	x	x
Children aged 0–5		x					x
Empl. in construction		x					x
GDP per employee							x
Log surface area		x					
Log population density			x	x	x	x	x
Pop. change 2001–2011			x	x	x	x	x
Self-employed				x	x	x	
Unemployment		x				x	
Youth empl. 15–29			x	x		x	
Youth unemployment					x		x
# observations	231	231	231	231	231	231	231
# parameters	4	9	8	9	9	10	11
R^2	.167	.373	.305	.305	.331	.321	.372
Adjusted R^2	.156	.351	.283	.280	.307	.293	.344
First-stage F-statistic	6.70	2.27	9.98	9.97	10.08	11.35	9.37

Notes: The table presents the OLS estimates of γ_1 in model (3) for the seven specifications presented in Table 2, their heteroskedasticity-robust standard errors in parentheses, and their 95% confidence intervals in brackets. Point estimates, standard errors and confidence intervals for all other coefficients are available from the Authors upon request. All specifications include the constant term and binary indicators for municipal capital and coastal municipality.

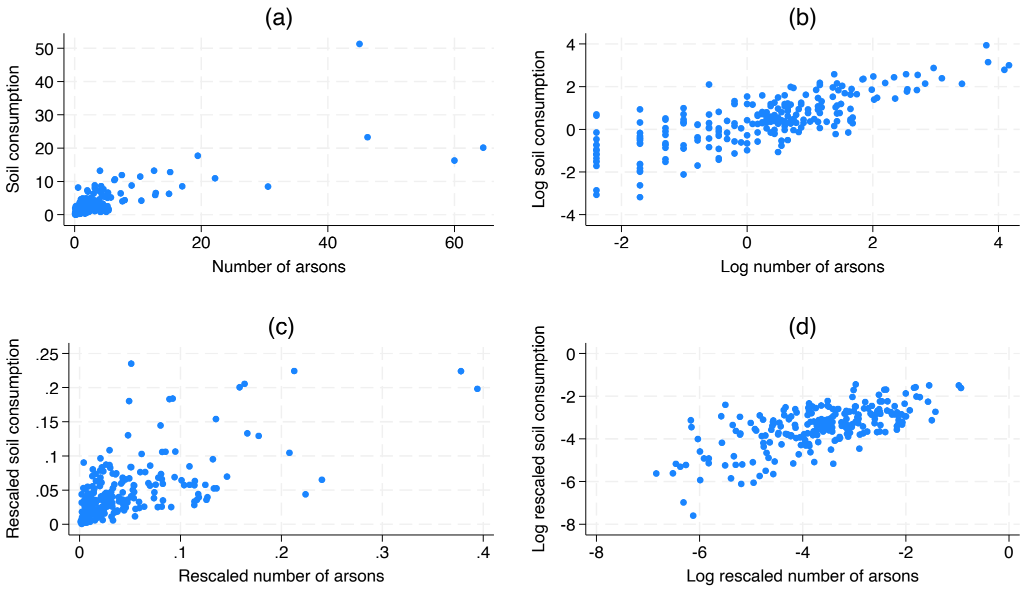
Figure 1: Soil consumption and arsons in Apulia

(a) (b)



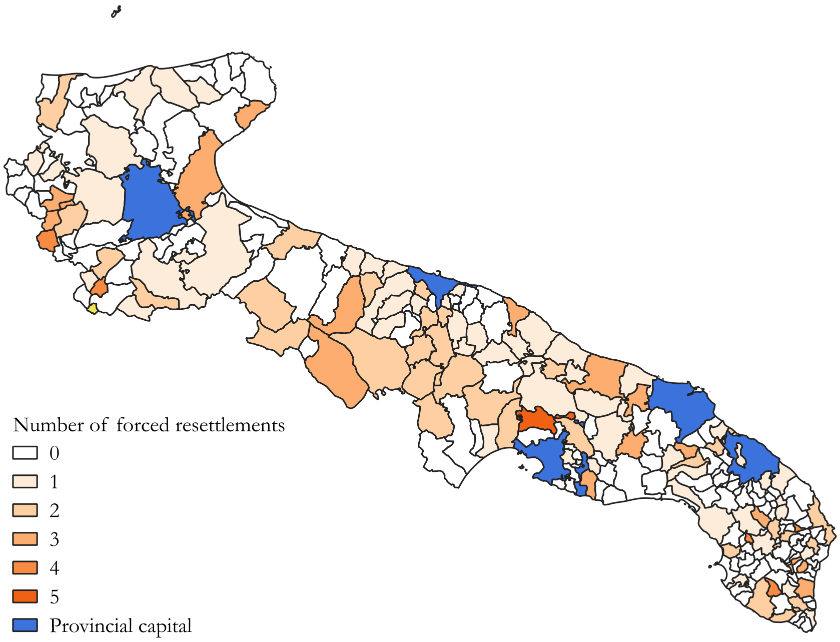
Notes: Panel (a): Soil consumption, 2006–2018. Panel (b): Total number of arsons, 2004–2014.

Figure 2: Scatterplots of annual soil consumption during 2006–20018 and the annual number of arsons during 2004–2014 for the Apulian municipalities.



Notes: Panel (a): Soil consumption and number of arsons. Panel (b): Log soil consumption and log number of arsons. Panel (c): Soil consumption and number of arsons rescaled by the municipality's surface area. Panel (d): Log rescaled soil consumption and log rescaled number of arsons.

Figure 3: Number of forced resettlements between 1956 and 1995 by municipality.



A Data appendix

A.1 Soil consumption data

The Italian National System for Environmental Protection (*Sistema Nazionale per la Protezione dell'Ambiente* or SNPA) monitors environmental problems at the territorial level and, among other things, produces high-quality data on soil consumption. In doing this, the SNPA exploits the potential of the European Union (EU) space program, specifically its Earth observation component called Copernicus. Copernicus offers information services drawn from satellite Earth observation and non-space data. It is managed by the European Commission and is implemented in partnership with the EU member States, the European Space Agency, the European Organization for the Exploitation of Meteorological Satellites, the European Center for Medium-Range Weather Forecasts Mercator Ocean International, and various other EU agencies.

Copernicus' satellites provide high-resolution optical and radar images of the Earth, allowing monitoring of the territory. SNPA uses the multi-spectral images of Sentinel-2 satellite (13 bands) characterized by a high revisit time (3–5 days) and a resolution between 10m and 60m, along with the radar images of Sentinel-1 satellite, which can image Earth's surface also through rain and cloud, and regardless of sun light presence. Both images, with appropriate pre-processing, make it possible to develop automatic and semi-automatic classification procedures, which are at the basis of subsequent photo-interpretation, processing and cartographic restitution.

SNPA monitoring produces a national map of land consumption on a 10x10m raster basis (regular grid) which divides the entire national territory into consumed land and non-consumed land. Artificial surfaces are detected only if they are large enough to cover more than 50% of a 10x10m cell. The monitoring exercise is annual, follows a homogeneous methodology, and involves a stepwise process consisting of the following phases: acquisition of input data (Sentinel-1 and 2, other available satellite images, ancillary data); data pre-processing; semi-automatic classification of the complete time series of the current year and the previous year of Sentinel-1 and 2; production of a preliminary cartography; complete multi-temporal photo-interpretation of the entire territory and detail-scale editing (greater or equal than 1:5,000); review of the historical series; rasterization; validation; national mosaicking and re-projection in an equivalent system; processing and return of data and indicators. For further details see Luti et al. (2021).

A.2 Arson data

Arson data are produced by the Italian National Fire and Rescue Service (*Corpo Nazionale dei Vigili del Fuoco* or CNVVF), which is organized into directorates (regional and inter-regional), provincial commands (present in each provincial capital), fire stations (*distaccamenti*), and fire-fighter teams. Each provincial command manages a variable number of fire stations. A large municipality may have multiple fire stations and several small municipalities may share the same fire station. The number and location of detachments at the provincial level depend on local population density, historical patterns of intervention, and the presence of activities with a significant risk.

Each fire-fighter intervention is associated with an intervention report (*rapporto di intervento*): a document containing the relevant data of the intervention (date, time, address, etc.) and a descriptive account. The report is compiled by the team manager upon his return to the fire station and then reviewed by an officer in the provincial command (*funzionario di guardia* or FDG). In the organization chart of the CNVVF, reaching the FDG position represents a significant career advancement and requires 25 years of operation. Each province has its own FDG who is in charge of training activities for team managers, plus two additional functions: checking that each intervention report is properly prepared and then formally closing it. As a result, interventions reports are comparable across provinces.

A.3 Other data on the local strength of organized crime

The data on the number of cases of threat or intimidation against local public administrators are produced by *Avviso Pubblico–Enti Locali e Regioni Contro Mafie e Corruzione*, an association promoting transparency and integrity in public administrations that closely monitors instances of intimidation and threat against local administrators. *Avviso Pubblico* is regularly heard by the Italian Anti-Mafia Parliamentary Committee and is a member of the Ministry of the Interior National Observatory on the Intimidation of Local Administrators. We use data on the number of cases of threat or intimidation other than arson, including sending envelopes, emails or faxes containing threatening letters or bullets; leaving bullets in front of a private home or at the town hall; writing threatening or insulting text on the homes/municipality walls or on the graves of relatives of the targeted person; gunfire against a private car or home, or at the town hall; damage and theft within the town hall; physical assault in a public place; killing personally owned animals; sending a severed animal head in a box; and cutting down privately owned fruit trees.

The data on the number of real estate properties seized from mafias by the judicial authority, confiscated and transferred to municipal authorities are produced by a national public agency (*Agenzia Nazionale per l'Amministrazione e la Destinazione dei Beni Sequestrati e Confiscati* *alla Criminalità Organizzata*). The types of real estate considered include apartments, villas, properties designated for commercial and industrial purposes, warehouses or storage spaces, boxes, garages, parking spaces, and land.

The data on the number of mafia clans (criminal associations consisting of one or more mafia families) are based on a census conducted at the municipality level by the Anti-Mafia Investigative Directorate (*Direzione Investigativa Antimafia* or DIA), an investigative agency of the Ministry of the Interior. Since 2013, the semi-annual DIA reports contain provincial maps with the municipalities in which the mafia clans operate and the name of the clans.

The data on the number of innocent mafia victims are produced by *Libera–Associazioni, Nomi e Numeri Contro le Mafie*, a network that includes associations, social cooperatives, schools, unions, parishes, etc. *Libera* made crucial contributions in the fight of mafias by informing and mobilizing the civil society, including decisive support in favor of Law 109 in 1996 establishing that assets confiscated from mafias can be reused for social purposes. It is present throughout Italy in 20 regional coordination offices, 83 provincial coordination offices, and 304 local outposts.

Table A.1: Name and definition of all control variables.

Name	Definition	Source	Years
Activity Index	Ratio between labor force and population aged 15+	ISTAT MD	2001
Aged 15–19 with secondary degree	Fraction of residents aged 15–19 with lower/upper secondary school degree	ISTAT PCD	2001
Aged 30–34 with university degree	Fraction of residents aged 30–34 with university degree	Istat PCD	2001
Aging index	Ratio between the number of residents aged 65+ and the number of residents aged 0–14	Istat PCD	2001
Children aged 0–5	Ratio between the number of residents aged 0–5 and the total number of residents	Istat PCD	2001
Coastal municipality	Binary indicator equal 1 if a municipality borders the sea coast, and 0 otherwise		
Empl. in construction	Fraction of employed residents in the construction industry	Istat MD	2001
Empl. in manufacturing	Fraction of employed residents in the manufacturing industry	Istat MD	2001
Empl. in non-retail services	Fraction of employed residents in non-retail services (e.g. education, health care and financial services)	Istat PCD	2001
Empl. in services	Fraction of employed residents in the services	Istat PCD	2001
GDP per employee	GDP divided by total employment	RUR (2004)	2001
High education	Holders of high school diploma or bachelor's degree divided by total number of residents aged 6+	Istat MD	2001
Low education	Illiterates, literates w/o qualif. and holders of primary school degree divided by number of residents aged 6+	Istat MD	2001
Pop. change 2001–2011	Difference btw. the number of residents in 2011 and 2001	Istat PCD	2001, 2011
Population density	Number of residents per square kilometer	Istat PCD	2001
Population size	Number of residents	Istat PCD	2001
Provincial capital	Binary indicator equal 1 if the municipality is a provincial capital, and 0 otherwise		
Self-employed	Fraction of employed residents who are self-employed	Istat MD	2001
Surface area	Surface area in square kilometers	Istat MD	2001
Unemployment	Fraction of active residents aged 15+ who are unemployed	Istat MD	2001
Youth empl. 15–29	Fraction of residents aged 15–29 who are employed	Istat PCD	2001
Youth unemployment	Fraction of active residents aged 15–24 looking for a job	Istat PCD	2001

Notes: Istat PCD is the Istat Population Census Database, Istat MD is the Istat Municipality Database.

B Additional tables

Table B.1: Logistic regressions of the forced resettlement indicator on alternative sets of pre-1956 covariates.

Covariate	L1	L2	L3	L4	L5	L6
Aged 65+	-1.724		-1.541		-1.368	
	(2.242)		(2.234)		(2.237)	
Aging index		5.047		4.441		5.182
		(2.873)		(2.943)		(2.94)
Coastal municipality	.069	.134	.011	.076	.062	.124
	(0.311)	(.321)	(.313)	(.322)	(.311)	(.319)
Employment in agriculture	1.319	1.447				
	(1.741)	(1.759)				
Employment in construction					9.182	11.703
					(11.964)	(12.139)
Employment in services			2.776	5.045		
			(10.08)	(9.65)		
High school/bachelor degree			46.411	38.102		
			(24.456)	(25.191)		
Illiteracy rate	-1.431	-.843			-.996	-.303
	(3.104)	(3.065)			(3.087)	(3.084)
Labor force participation rate	-2.436	-2.597	0.289	.371	-.966	-.937
	(2.008)	(2.01)	(1.695)	(1.666)	(1.429)	(1.414)
Population density	-.001	-0.001	-.002	-.002	-.001	-.001
	(.001)	(0.001)	(0.001)	(0.001)	(0.001)	(.001)
# observations	226	226	226	226	226	226
# parameters	7	7	7	7	7	7
Pseudo R^2	.0111	.0217	.0278	.0357	.0111	.0224

Notes: The table reports the results of estimating various logit specifications based on alternative sets of demographic and socio-economic covariates referring to the year 1951. For each specification, the table presents the estimates of the coefficient on the covariates and their heteroskedasticity-robust standard error (in parentheses). Provincial capitals are excluded from the sample because the law prohibited them from hosting resettled mafia bosses.

Covariates description: Population density is the number of residents per square kilometer; Aging index is the ratio between the number of residents aged 65+ and the number of residents aged 0–14 years; Aged 65+ is the ratio between the resident population aged 65+ and the total resident population; Coastal municipality is a binary indicator equal 1 if the municipality borders the sea coast, and 0 otherwise; High school/bachelor is the ratio of the population with a diploma or degree to the resident population aged 6+; Illiteracy rate is the fraction of the population aged 25–64 years that is illiterate; Employment in construction is employment in the construction industry as a percentage of the resident population aged 10+; Employment in agriculture is employment in agriculture, hunting and fishing as a percentage of the resident population aged 10+; Employment in services is employment in transportation and communications, trade and miscellaneous services, credit and insurance, and public administration as a percentage of the resident population aged 10+.

Table B.2: Balancing tests on the pre-1956 covariates included in the logistic regressions for the forced resettlement indicator.

Covariate	μ_1	μ_0	t-stat	p-value
Aged 65+	.078	.075	.568	.571
Aging index	.243	.255	-1.659	.099
Coastal municipality	.252	.273	-.350	.727
Employment in agriculture	.392	.390	.081	.935
Employment in construction	.022	.023	-1.025	.307
Employment in services	.063	.068	-1.559	.120
High school/bachelor degree	.017	.020	-2.263	.025
Illiteracy rate	.260	.257	.502	.616
Labor force participation rate	.588	.572	1.076	.283
Population density	230.0	207.8	1.029	.305
# observations	99	127		

Notes: The column labeled μ_1 reports the covariate mean for the municipalities that hosted at least one resettled mafia boss in 1956–1995, while the column labeled μ_0 reports the covariate mean for the municipalities that did not host any resettled mafia boss. Provincial capitals are excluded from the sample because the law prohibited them from hosting resettled mafia bosses. The last two columns report the t-test statistic for the equality of the means and the two-sided p-value of the test.