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Social Closure, Surnames and Crime

Highlights

- Study of the effect of social closure on crime rates;
- Use of very disaggregated data for Italian municipalities;
- Use of an original and innovative measure of social closure based on the diversity of surname distribution;
- Results support the view that social closure favors limited as opposed to generalized morality
- Social closure strengthens cooperation at the local level, but hampers cooperation with strangers

Social Closure, Surnames and Crime*

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March 2, 2017

Abstract

This paper studies the effect of social closure on crime and tax evasion rates using disaggregated data for Italian municipalities. We propose an original and innovative measure of social closure based on the diversity of surname distribution, which reflects a community's history of migration and inbreeding. We find that, all else equal, communities with a history of social closure have lower crime rates and higher tax evasion rates than more open communities. The effect of social closure is likely to be causal, it is relevant in magnitude, statistically significant, and robust to changes in the set of included controls, in the specific measures of dependent and independent variables, in the specification of the regression equation, and in the possible sample splits. Our findings are consistent with the idea that social closure strengthens social sanctions and social control, thus leading to more cooperative outcomes in local interactions, but it reduces cooperation on a larger scale.

JEL-Classification: A14, K42, Z13

Key-words: Social Closure; Surname Distribution; Crime

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1 Introduction

The traditional economics of crime, that stemmed from the seminal paper by Becker (1968), focused on the deterrent effect of punishment devoting little attention to the social and informal determinants of criminal behavior. Recent literature has increasingly addressed this issue. Weber (1978) defines social closure as the tendency of a group to restrict entry to outsiders. Sociologists and economists have long recognized its role in shaping pro- and anti-social behavior. Some scholars (e.g., Durkheim, 1893; Posner, 1997; Allcott et al., 2007) emphasize that, by intensifying repeated interaction, strengthening social sanctions and favoring collective action, social closure may raise social control and reduce crime.[1] Other scholars (e.g., Banfield, 1958; Platteau, 2000; Tabellini, 2008) suggest that the improvement in norm enforcement at the local level may come at the expense of cooperation on a larger scale, so that social closure may give rise to phenomena such as amoral familism or limited morality (as opposed to generalized morality), eventually hampering cooperation with strangers, economic exchange and development.[2] As discussed in Coleman (1988), Putnam (2000) and Allcott et al. (2007) community size is extremely relevant in affecting prosocial behavior, suggesting that social closure may facilitate cooperation and increase trust among individuals. This is due to the fact that social sanctions are stronger in socially closed networks. Empirical progress has been limited by the difficulty to overcome two main challenges: finding a credible measure of social closure for large samples and establishing its causal impact on crime rates.

This paper examines the relationship between social closure and crime rates using very disaggregated data for Italian municipalities. We deal with the empirical issues proposing a new measure of social closure. Our approach borrows from the human biology and genetic literature and measures the degree of openness of a community by the diversity of its surname distribution, which reflects a community's history of migration and inbreeding. As we detail in Section 2, relative to competing measures of social closure, ours has the advantage of being more direct and disaggregated, as well as of being available for large samples.

We document a positive and significant correlation between a municipality's crime rates and the diversity of its surname distribution. This correlation is relevant in magnitude, robust to alternative specifications, it has high explanatory power, and it is always strongly significant but in cities, where interaction is more anonymous. At the same time, we also document a negative, significant and robust correlation between surname diversity and the TV tax evasion rate. The latter is due by all households that own a television, which are virtually the totality of households, and finances TV broadcasting of public national channels, which is essentially a national public

[1]Variations of these arguments include theories of anomie, social disorganization, social capital, reputation and retaliation. See also, among others, Shaw and McKay (1942); Coleman (1988); Sampson (1993); Elster (1989); Rasmusen (1996); Funk (2004); Falk et al. (2005); Buonanno et al. (2012); Bigoni et al. (2016).

[2]In principle, social closure might even foster crime through a number of channels, ranging from imitation of delinquent peers (Glaeser et al., 1996; Patacchini and Zenou, 2012) to know-how sharing among criminals (Calvó-Armengol and Zenou, 2004), to street culture (Silverman, 2004).

good since in practice no households are excluded. We thus find that, all else equal, communities with a history of social closure display lower crime rates at the local level but also lower contribution to national public goods than more open communities.

We argue that it is unlikely that these results are driven by reverse causality. It is more difficult to exclude that they are driven by omitted variables, associated to both historical social closure and to current crime rates and TV tax evasion rates. Yet, the robustness of the above results to changes in the set of included controls, in the specific measures of dependent and independent variables, in the specification of the regression equation, and in the possible sample splits, as well as their robustness to instrumentation by the presence of major Roman roads, suggest that omitted variables are not likely to drive them either.

Our evidence is consistent with the idea that social closure strengthens social sanctions and social control, thus leading to more cooperative outcomes in local interactions, but crowds out values of generalized cooperation, thus reducing cooperation on a larger scale. Since this is the effect of a strengthening in local enforcement predicted by Tabellini (2008), we see our results as supportive evidence for his model. The theoretical intuition is that, in a more closed community, precisely the fact that people interact more frequently and repeatedly with one another strengthens social sanctions and social control, and thus the incentive to cooperate locally, but at the same time it reduces the value of cooperation with strangers, with whom interaction is less frequent and the probability of being sanctioned if cheating is lower. Hence, social closure fosters cooperation with neighbors, but hampers it with strangers. Empirically, it reduces crime rates at the local level, but it also reduces private contribution to national public goods.

The remainder of the paper is organized as follows. In Section 2 we put our proposed measure of social closure in the context of other studies that have relied on information based on surnames. Sections 3 presents the data. Sections 4 and 5 display our baseline evidence and a number of robustness exercises. Section 6 concludes.

2 Social Closure and Surname Diversity

One of the main challenges in the empirical study of the effects of social closure is finding a credible and reliable measure, available for large samples. In this paper we propose an innovative and original approach based on measuring a community's social openness by the diversity of its surname distribution. In particular, we focus on surname entropy, but we also consider different statistics.

Under patrilineal transmission, apart for mutations, such as new surnames due to misspelling or to voluntary changes, which are typically limited in number, over time a community's surname distribution essentially becomes more diverse when men with new surnames arrive from outside to form new households, whereas it becomes less diverse when men either leave the community or inbreed (that is, form new households with women of the same community), in the latter case because surnames tend to disappear due to the positive probability of having no male offspring. Thus, a community with a history of closure ends up with a highly concentrated surname distribution, whereas one with a history of openness will have a more diverse distribution.

In Italy, as in many Western societies, surnames are vertically transmitted from fathers to children.[3] This property makes them a precious source of information on vertically transmitted genetic or cultural traits, as long recognized by the literature in human biology, genetics and anthropology.[4] Economists have so far underutilized this source of information. A notable exception is Güell et al. (2015), who study intergenerational mobility, but we differ from them in that, rather than on the informational content of *individual* surnames, we focus on the diversity of the *distribution* of surname, which reflects a community's history of male migration and reproduction patterns.

We extract the distribution of surnames from the national telephone directory of the year 1993 (SEAT - Società Elenchi Abbonati al Telefono). The number of individual subscribers (18,546,891) amounts to around 33% of the whole population of 1993, virtually covering all Italian households. For each municipality, we thus have its entire surname distribution in 1993. We also have the distribution of its ten most frequent surnames in 2004.[5] Our main measure of diversity, *Entropy*, is defined as follows:

$$Entropy = -\sum_{i=1}^{S}(p_i \log p_i),$$

where S is the total number of surnames in a municipality, and p_i is the municipality's population share with a given surname. This measure of entropy is used in information

[3]The origin and diffusion of Italian surnames are related to the Ecumenical Council of the Roman Catholic Church held in Trento (Italy) from 1545 to 1563. After the Council of Trento, all parishes had to keep exhaustive birth and marriage records (death and census records became compulsory in 1614). Even if the late 16th century can be considered the beginning of Italian surnames, temporal differences exist over the country. While in rural or mountainous areas (e.g., the Central Apennines) their use started in the 16th/17th century, birth and marriage records are documented in several urban areas (e.g., Venice and Florence) as early as the 12/13th century. As in other European countries, prominent social groups generally had family names long before lower social classes. Anyway, the majority of Italian surnames can be traced back to the beginning of the 17th century and have a time depth of at least four centuries.

[4]The parallelism between paternally inherited genetic characters and names was first recognized by Darwin (1875), who estimated the frequency of first cousin marriages from the proportion of isonymous unions. Crow and Mange (1965) developed the idea that the degree of inbreeding in a population could be calculated from the frequency of isonymous marriage, leading to a stream of population studies (see, e.g., Lasker, 1968; Gottlieb, 1983; Barrai et al., 1999). Studies in anthropology and genetics have found that the distribution of surnames in patrilineal societies is similar to that of the neutral alleles of a gene transmitted only through the Y-chromosome (Yasuda and Morton, 1967; Yasuda and Furusho, 1971; Yasuda et al., 1974; Zei et al., 1983a,b), and indeed to that of any social or cultural trait, which is vertically transmitted from father to children and does not provide an intrinsic reproductive advantage (Cavalli-Sforza and Feldman, 1981; Cavalli-Sforza et al., 2004; Darlu et al., 2012). Crow (1983) states: "Surnames provide a quick, easy, cheap, and crude way to study human inbreeding and migration. Isonymy is the poor man's population genetics. A phone book is a lot less expensive than a battery of acrylamide gels, a shelf of restriction endonucleases, or a centrifugal fast analyzer."

[5]The number of individuals registered in the phone book remained fairly stable up to 2004. Until 2004 it was compulsory for all individuals holding a telephone landline to appear in the phone book. On July 15, 2004 the Italian Data Protection Authority made registration in the phone book voluntary.

theory to capture disorder within a system. It is also used in ecology and biology (where it is usually called Shannon-Weaver Diversity Index) to measure α diversity (within-habitat diversity): in our context, it can be interpreted as a weighted average of surname 'rarity', where surname i's 'rarity' is captured by $-\log p_i$ (implying almost infinite 'rarity' for p_i close to 0) and its weight is simply its population share p_i.

We also experimented with alternative statistics, such as the share of the first n most frequent surnames. These shares, with n from 1 to 5, are highly correlated with one another (their correlation is always above 0.9), so we display results only for *First Share*, which is the population share of the most frequent surname in a municipality. The correlation between *First Share* and *Entropy* is around -0.7: *First Share* captures homogeneity rather than diversity, and thus social closure rather than openness.[6] Figure 1 shows *Entropy* and *First Share* in 1993.

Between 1993 and 2004 Italy was interested by a relevant immigration flow, which reduced both the mean and the standard deviation of *First Share*. The correlation between the share of the most common surname in the two years, *First Share 93* and *First Share 04*, is above 0.9 (and the same is true for the share of the first n most frequent surnames, for n from 2 to 5). It thus seems that, while immigration has generally increased social openness, it has not substantially changed the informational content of municipality surname distribution.

Relative to network-based measures of social closure (see, e.g., Allcott et al., 2007; Karlan et al., 2009), our approach has the advantage of not requiring information on individual connections, which is typically not available on a large scale. Relative to more indirect empirical proxies of closed networks, such as the proportion of county population living in small towns (see, e.g., Goldin and Katz, 1999; Buonanno et al., 2012), it has both the advantage of being more disaggregated and that of being more closely derived from the migration and social interaction dynamics that drive social closure.

3 Crime and Municipality Characteristics

Our unit of observation is the municipality (*comune*). Data at the municipality level for Italy are available from different sources. The main advantage of using municipality level data is represented by a much finer disaggregation than the one commonly used in economic investigations of crime, which are mostly conducted at the county (or NUTS3 or province) level. For each of Italy's more than 8,000 municipalities, we consider the average crime rate across the period 2004-2010 for different crime categories: *total crime*, *theft*, *car theft*, *burglary*, *robbery* and *serious assault*. These are shown in Figures 2 and 3. Data have been confidentially obtained by the statistics

[6]We also computed the fractionalization index, defined as *Fractionalization* $= 1 - \sum_1^S p_i^2$, which is another measure of diversity commonly used in the economic literature. Yet, this is not a good measure of surname diversity, due to the fact that it converges very fast to 1 as S increases. Due to the high number of distinct surnames, *Fractionalization* has mean 0.98 and standard deviation 0.02. This low variability makes it unsuitable to capture differences in surname diversity. Formally, observe that if each surname's share is $p = 1/S$, then *Fractionalization* $= 1 - 1/S$, whereas *Entropy* $= \log S$.

department of the Italian police. Data for the TV tax evasion rate have been obtained from Italy's national public broadcasting company (*RAI - Radiotelevisione Italiana*) and are available over the period 2004-2010. Our variable of interest (*Tax Evasion*) is the fraction of a municipality's households that do not pay the television tax.[7] It is displayed in Figure 4.

Our dataset also includes a set of control variables that are likely to be correlated to crime rates, illegal behavior and to the distribution of surnames, so that their exclusion might give rise to an omitted variable bias. These variables belong to four domains: geographic, socio-economic, demographic and deterrence variables. Descriptive statistics are presented in Table 1.

The geo-morphology of a municipality may affect both the incentives to commit crimes (for instance by providing hiding places or escape opportunities) and the distribution of surnames (for instance by limiting access from other municipalities and thus favoring inbreeding and surname concentration). We thus include among the controls, for each municipality, the share of mountainous territory (*Mountain Share*), average altitude (*Altitude*), difference in altitude between the highest and the lowest locations in a municipality (*Altitude Difference*), ruggedness (*Ruggedness*), distance from the sea (*Sea Distance*), and a dummy assuming value 0 for municipalities along the coast and 1 for those without direct access to the sea (*Landlocked*). All geo-morphological controls but ruggedness are available from the Italian Institute of Statistics (*ISTAT*). The municipal measure of terrain ruggedness has been constructed from the Global Land One-km Base Elevation Project (GLOBE), a global gridded digital elevation data set covering the Earth's surface at a 10-minute spatial resolution (approximately 1km).[8]

Socio-economic controls include first of all average income per capita (*Income*), which affects legitimate and illegitimate earning opportunities (Ehrlich, 1973; Buonanno, 2006) and is also related to surname diversity, as we document below. Per capita income is made available by the Italian Ministry of Economy and Finance (*MEF*) at the municipality level. We consider the average over the period 2004-2010. In addition, our socio-economic controls include information at the municipality level on human capital, which is often found to be significantly associated to crime (Lochner, 2011). Human capital is measured by the share of high school and of college graduates (*High School* and *Graduate*). Data on education are taken from the 2001 Census produced by the *ISTAT*. Demographic controls include, for each municipality, its population and surface (*Population* and *Surface*), to capture population density, which is typically associated to higher crime rates and to higher surname diversity (Glaeser and Sacerdote, 1999; Buonanno et al., 2012); the share of males by 5-year-age brackets (*Male Age Shares*), to capture the different propensity to commit crimes of different age groups (Freeman, 1991; Grogger, 1998), and finally the share of male immigrants (*Immigrant*

[7] The Italian television tax is due by all families owning a television, which essentially means by all families, but it is very weakly enforced. Its payment depends on the willingness to contribute to a national public good, that is, on the sense of civic duty.

[8] The GLOBE data set has superseded the GTOP30, which before the introduction of GLOBE was considered the most accurate digital elevation data set and has been used, among others, by Nunn and Puga (2012).

Male Share) and a measure of openness, given by (immigrants+emigrants)/population (*Openness*), to control for their effects on both surname diversity and crime (Bianchi et al., 2012). Demographic variables are taken from *ISTAT* and refer to the average across the period 2004-2010.

As a deterrence variable at the municipality level we use the presence in 2010 of a police (*Carabinieri*) station (*Police*) obtained from the official website of *Carabinieri* (Italian Gendarmerie).[9] As there were no police reforms during the period of interest, such information is also representative of the presence of police stations in previous years.

Finally, in our analysis we consider a local labor system (*SLL*) dummy. The local labor system is a statistical unit that encompasses neighboring municipalities (on average slightly more than 10), across which people usually commute between home and work place. They are defined by *ISTAT* using information on commuting habits from the Census. We use *SLL* dummies based on the 2011 Census. Inclusion of such dummies allows controlling for factors such as the rural or urban nature of a municipality or its distance from the closest big city, factors that are likely to be related to both social closure and crime rates.

4 Baseline Evidence

We take advantage of the rich and disaggregated data at hand to identify the effect of social closure on crime and tax evasion. Our baseline evidence comes from estimating through ordinary least squares (OLS) a regression model of the following form:

$$y = \beta s + X\gamma + \epsilon, \tag{1}$$

where for each municipality i, y_i is either its crime rate or its TV tax evasion rate; s_i is a summary statistic of its distribution of surnames, capturing either diversity (*Entropy*) or concentration (*First Share*); and X_i is a set of controls.[10] Our coefficient of interest is β. Tables 2 to 4 report its OLS estimate, $\hat{\beta}$, for different specifications of y, s and X.

Table 2 displays our baseline evidence on the association between social openness and crime rates. The top panel reports the coefficient of *Entropy*, $\hat{\beta}$, estimated from equation (1) in different regressions. Rows correspond to the dependent variables indicated on the left: *Total Crime*, *Theft*, *Car Theft*, *Burglary*, *Robbery* and *Serious Assault*. Columns correspond to the different sets of included controls specified in the bottom panel. Column (1) shows the simple correlation between *Entropy* and the different crime rates, without controlling for any covariate (but for a constant, which is always included although not displayed). Column (2) introduces geographic controls (*Mountain Share*, *Altitude*, *Altitude Difference*, *Ruggedness*, *Sea Distance*, *Landlocked*) and 103 province dummies. Column (3) adds *Population* and *Surface* to control for

[9] http://www.carabinieri.it/

[10] With usual notation, y, s and ϵ are N-dimensional column vectors, β is a scalar, X is an NxK matrix, and γ is a K-dimensional column vector.

population density. Column (4) adds *Income*. Columns (5) to (8) progressively add *Male Age Shares*, proxies for migration (*Immigrant Male Share* and *Openness*), deterrence (*Police*), and education (*High School* and *Graduate*). Column (9) replaces province dummies by 686 SLL dummies. Standard errors are clustered at the province or SLL level whenever the corresponding dummies are included.

Column (1) shows that, without controlling for any covariate, *Entropy* is positively and significantly correlated with all crime rates. Even alone, *Entropy* has high explanatory power: the R^2 of the various regressions in column (1) (not displayed for the sake of space) lies between 7% (for *Robbery*) and 23% (for *Theft*). Moreover, the estimated coefficients are relevant in magnitude: a standard deviation increase in *Entropy* is associated to rises in crime rates between 1/4 of a standard deviation (for *Robbery*) and 1/2 of a standard deviation (for *Theft*).[11]

To put these figures in perspective, it may be useful to compare them with the corresponding ones for *Income*. A simple regression, without covariates, of crime rates on *Income* (not reported for the sake of space) always returns a positive and significant coefficient. For all crime rates, but for *Burglary*, the explanatory power of *Income* is lower than that of *Entropy*. Further, even the magnitude of the association between *Income* and crime rates is smaller than that with *Entropy*, again with the exception of *Burglary*.[12]

Columns (2) to (9) of Table 2 progressively include additional controls and up to almost 700 local area dummies. *Entropy*'s sign and significance is confirmed for all crimes and specifications. Even the magnitude of the estimated coefficient is little affected by different specifications, although it tends to be smaller in the full specification than in the unconditional one.[13] The implication is that the strong and positive statistical association between *Entropy* and all crime rates does not seem to be driven by omitted variables.

To have an overview of the effects of the covariates, Table 10 in the Appendix reports in columns (1) to (6), for each crime, the estimated coefficient of *Entropy* and of all the controls included in the full specification of column (9) of Table 2. While the effect of some covariates is quite robust across crimes and in line with expectations (for instance, crime rates tend to be lower in the mountains, whereas they tend to be higher along the coast and in more populated municipalities), other coefficients, even when significant, should be interpreted with caution, as they might reflect reverse causation and omitted variables (for instance, a police station may be placed where there is more crime, and higher levels of economic activity may drive the correlation of crime with

[11] In detail, a standard deviation increase in *Entropy* is associated to rises by around 0.4 of a standard deviation for *Total Crime*, *Car Theft* and *Serious Assault*, and by 1/3 of a standard deviation for *Burglary*.

[12] The R^2 ranges from 1% (for *Serious Assault*) to 18% (for *Burglary*), and it is always lower than 7%, but for *Theft* (15%) and *Burglary*. A standard deviation in *Income* is associate to rises in crime rates by 1/10 (for *Serious Assault*), 1/5 (for *Car Theft*), 1/4 (for *Total Crime*) and 2/5 (for *Theft* and *Burglary*) of a standard deviation.

[13] For instance, in the specification of column (9) a standard deviation increase in *Entropy* is associated to a rise by around 0.4 (for *Serious Assault*), 0.3 (for *Total Crime* and *Car Theft*), 0.25 (for *Theft*), 0.17 (for *Robbery*) and 0.08 (for *Burglary*) of a standard deviation.

openness and education). Since our purpose is not to identify the causal effect of the controls, but rather to use them to minimize the risk that the correlation with *Entropy* is driven by omitted variables, we do not discuss the role of the other controls any further.

Table 3 explores to what degree the correlation between crime rates and social openness is driven by the use of *Entropy* as a measure of surname diversity. It is structured as Table 2, but it substitutes *First Share* for *Entropy*, thus focusing on surname concentration (a measure of social closure) rather than on diversity (a measure of openness). Since this alternative explanatory variable is available for two years, Panels A and B respectively report the estimated coefficient of *First Share 04* and of *First Share 93*, which are very similar to one another in terms of sign, significance and magnitude. The explanatory power of *First Share* is lower than that of *Entropy*.[14] This is not surprising, since *First Share* only uses information on the population share of the most common surname, whereas *Entropy* exploits information on the entire surname distribution.

For all crimes and specifications, and for both years, the displayed coefficients in Table 3 are negative; most of them (around 90%) are also significant.[15] As it is true for explanatory power, also the magnitude of the association with crime rates is somewhat smaller for *First Share* than for *Entropy*.[16] Overall, the results based on *First Share* are in line with those based on *Entropy*, and suggest that we are capturing a robust relationship between social closure and crime. Analogous regressions with the share of the n most common surnames, for $n = 2, ..., 5$, yield very similar results.[17] The main difference, noticed above, is that *First Share* has less explanatory power than *Entropy* for crime rates, and yields effects of smaller magnitude.

Table 4 turns to the investigation of the TV tax evasion rate and its association with surname distribution. It has a similar structure to Tables 2 and 3, but it displays the OLS estimate of β in regressions of the TV tax evasion rate on the explanatory variable, which is *Entropy*, *First Share 04* and *First Share 93* in Panels A, B and C, respectively, and on the controls specified in the bottom panel. Independently of the chosen statistic for the distribution of surnames, and of the specification of included controls, TV tax evasion is significantly lower in municipalities with higher social openness (and significantly higher in municipalities with higher social closure). Even the magnitude of

[14]For instance, the R^2 of the regression of *Total Crime* in column (1), without covariates, on *First Share 93* and on *First Share 04* is 6% and 5%, respectively, whereas the analogous figure for *Entropy* (from the regression in column (1) of Table 2) is 16%.

[15]In 1993, the year in which *Entropy* is measured, Panel B shows that the only exception is the regression of *Robbery*, for which *First Share 93* is not significant in some specifications. Panel A shows that the significance of *First Share 04* depends on the specification also in the regressions of *Car Theft* and *Burglary*. Such reduction in significance is likely due to the fact that between 1993 and 2004 immigration reduced both the mean and the standard deviation of *First Share*.

[16]For instance, in the full specification of column (9), a standard deviation increase in *First Share 93* and in *First Share 04* are associated to a reduction in *Total Crime* by 8% and 6% of a standard deviation, respectively, whereas the corresponding figure for *Entropy* (from the regression of column (9) of Table 2) is a rise in *Total Crime* by 28% of a standard deviation.

[17]These results are not reported for the sake of space, but are available upon request. As already mentioned, we also experimented with fractionalization, but this measure displays too little variability.

the estimated coefficients does not substantially change across specifications, suggesting that surname diversity and concentration are almost orthogonal to other municipality characteristics, and thus providing no support for the possibility that their correlation with TV tax evasion is driven by omitted variables. Even alone, surname diversity has high explanatory power for TV tax evasion, and their association is relevant in magnitude: in column (1), the R^2 of the regression with *Entropy* is 9%, and a standard deviation increase in *Entropy* is associated to a reduction in TV tax evasion by 30% of a standard deviation.[18]

Taken together, our baseline evidence shows that social closure has substantial explanatory power (generally higher than standard economic correlates of crime such as income), and that it is associated to lower crime rates, but higher TV tax evasion rates. This correlation is statistically significant, relevant in magnitude, robust to alternative specifications, and, at least on the basis of the analysis carried out so far, it does not appear to be driven by omitted variables. Before interpreting these results, in the next section we present a number of additional analyses to tackle the possible threats to their validity and further corroborate them.

5 Robustness Checks

5.1 Estimates by subsamples and spatial analysis

In this section, we perform several alternative specifications designed to test the robustness of our estimates. For the sake of space, we focus on *Entropy* and we consider both its association with crime rates and with TV tax evasion rates.

First, we re-run our regressions by splitting the sample in various ways (by north-center-south and by village-town-city). While the previous analysis already suggests that the association between *Entropy* or and crime rates is not driven by omitted variables, it is still possible that the above results hide differences in this relation across different subsamples. To explore this possibility, Table 5 replicates the analysis of Table 2 and of Table 4 panel A (now with the dependent variables presented by column), by splitting Italy in three macro-regions: north, center and south, respectively presented in panels A, B and C (the bottom panel still presents the included controls, which always correspond to the specification of column (9) in the previous tables). As it is apparent, the results are extremely stable across the three subsample. In all subsamples, for all types of crime and for all specifications of the controls, the sign and significance of *Entropy* are confirmed, and even the coefficient magnitude is fairly stable (the only exception is the coefficient of *Entropy* for tax evasion in the South, which is confirmed in sign and close in magnitude, but is just marginally not significant at conventional levels). Bigoni et al. (2016) find that differences in cooperative norms may explain the

[18]The R^2 of the regressions with *First Share* in column (1) is between 5% and 6%. A standard deviation increase in *First Share* is associated to a reduction in TV tax evasion between 20% and 28% of a standard deviation. By comparison, the R^2 of a regression of TV tax evasion on *Income*, without controls, is 6%, and a standard deviation increase in *Income* is associated to a reduction in TV tax evasion by 1/4 of a standard deviation: roughly the same magnitudes found for social closure.

Italian North-South divide. Our results are in accordance with theirs, but also show the importance of differences in cooperative norms even within each macro-region.

Table 6 presents another way of splitting the sample, by municipality size. It has the same structure as Table 5, but it presents in panels A, B and C the coefficient of *Entropy* for villages, towns and cities, respectively defined as municipalities with less than 10,000, between 10,000 and 50,000, and with more than 50,000 inhabitants. The correlation of social closure with crime and tax evasion becomes less significant as municipality size increases: the coefficient of *Entropy* is always significant in villages, mostly significant in towns (except for *Burglary* and *Tax Evasion*) and never significant in cities (except for *Robbery*). Whenever it is significant, it is also confirmed in sign as in the baseline analysis. In terms of magnitude, it is highest for the towns subsample.

Second, the standard assumption of observation independence is hardly granted with municipality-level data.[19] We deal with this aspect not only by clustering the standard errors at the province or at the SLL level whenever we include corresponding area dummies, but also, and more importantly, by carrying out a spatial regression analysis, which takes into account that unmodeled spatial dependence in the error term reduces the efficiency of the estimator, whereas an unmodeled spatial lag may lead to biased estimates of β (Anselin, 1988; LeSage and Pace, 2009). As discussed above, it is likely that municipality-level observations are not independent from one another. More specifically, we estimate a spatial model using the generalized spatial two stage least squares (GS2SLS) estimator of Kelejian and Prucha (1998). Table 7 thus presents estimates of β obtained from the spatial model. In particular, it displays results from a spatial autoregressive model (panel A), a spatial error model (panel B) and a model with both spatial autoregressive and spatial error terms (panel C), estimated with a geodesic distance matrix. Each column corresponds to a regression of a specific crime or tax evasion rate (reported on the top) on *Entropy*, the spatial terms included in each model, and SLL dummies. The coefficients of the spatial terms (λ for the spatial lag and ρ for the spatial error) are mostly insignificant, suggesting that spatial correlation is not relevant. Most importantly, for each spatial model and type of crime, the coefficient of *Entropy* is positive and significant (negative and significant for tax evasion), showing the robustness of our previous results to the spatial analysis.

[19] To name just one reason, many people commute to neighboring municipalities to work and this may create a spatial correlation due to the mobility of either criminals or their victims. It may then be the case that neighoring municipalities exhibit similar crime rates, making the errors in model (1) correlated across neighbors and calling for a spatial error model to increase the efficiency of the estimator. It is also possible that crime rates in a municipality are directly affected by crime rates of neighboring municipalities, for instance due to know-how sharing among criminals (Calvó-Armengol and Zenou, 2004), to imitation of peer behavior (Glaeser et al., 1996; Patacchini and Zenou, 2005) or to potential victims' willingness to signal their readiness to self-defense (Silverman, 2004). In this case, model (1) would yield a biased estimate of β and a spatial lag model would be required (Anselin, 1988; LeSage and Pace, 2009).

5.2 IV strategy

Even after controlling for other determinants and for province and SLL fixed effects, crime and tax evasion rates may still be correlated with the error term. The standard concern is that the estimated effect of social closure may be biased due to reverse causality, omitted variables or measurement error. Reverse causality is plausibly a small concern, as crime or tax evasion rates are unlikely to determine the distribution of surnames. Such concern is even smaller after our analysis in Tables 3 and 4. There we show that results are robust to the use of predetermined statistics of the surname distribution, dating back to 1993, that is, around 10-15 years before our measures of crime and tax evasion, and also before the big immigration wave experienced by Italy since the Nineties. We have tried to minimize the concern for omitted variables through the inclusion of a long list of controls and through our robustness checks, and we know that measurement errors are close to zero for at least *Car Theft* and *Tax Evasion*. Yet, one can never be sure that no relevant variables are omitted, and for some crime rates measurement errors may still be a concern. As a consequence, we cannot exclude that our estimates are biased. In order to take these concerns into account, we adopt an instrumental variable approach that uses the historical presence of a major Roman road in the municipality territory.

Data on Roman roads have been constructed by scanning the Barrington Atlas of the Greek and Roman World (2000) and are available at the website Digital Atlas of Roman and Medieval Civilizations.[20] The construction of Roman roads is close to a natural experiment. As discussed in Dalgaard et al. (2015) and supported by the historical evidence, Roman roads were built for military purposes and for troops and army displacement over the wide territory of the Roman empire. Roman roads aimed at reducing travel time allowing a more rapid movements of army. For these reasons, Romans did not adapt roads construction to the environment, but tended to modify the environment for roads construction with a strong preference for straight roads. Several recent contributions have studied the legacy of historical road and transport network on population growth and suburbanisation (Baum-Snow, 2007; Michaels and Rauch, 2014). Carballo et al. (2014) studies the effect of infrastructure on trade instrumenting recent changes in the road network with the pre-Columbian Inca road network. Analogous approaches have been used by Duranton and Turner (2012) and Duranton et al. (2014) that take advantage of historical data on the railroad network and the exploration routes between 1528 and 1850 to analyze the effects of interstate highways on the growth of major US cities.

In our analysis, we consider that the presence of major Roman roads may have significantly affected the isolation of municipalities over time, considering that the wide majority of the Italian roads network is based on the historical Roman roads. Once equipped with this instrument for social closure, we proceed to analyze the effects on our measures of crime and tax evasion. Table 8 shows the results of our IV estimation that include SLL-fixed effects together with the list of controls previously described. It is precisely the inclusion of such long list of controls that reassures on the validity of

[20] http://darmc.harvard.edu/

the exclusion restriction. Moreover, controls include measures of isolation, so that our estimates can be interpreted as focusing on social closure, rather than on isolation per se. The first stage regression, reported in Panel A of Table 8, confirms the goodness of our instrument. The presence of a major Roman road is strongly significant and with the expected sign. The F-test for the excluded instrument is 44.8, suggesting that these estimates do not suffer from a weak instrument problem. Overall, 2SLS estimates are qualitatively consistent with the OLS results. Nevertheless, the magnitude of our IV estimates is higher than the corresponding OLS ones.

6 Discussion and Concluding Remarks

Let us now briefly summarize the contribution of this paper, discuss its interpretation, and present some suggestive evidence on its possible implications.

We present evidence that social closure is associated to lower crime rates and to higher TV tax evasion rates. We propose a new measure of social closure based on surname distribution. In particular, we measure a municipality's social openness by the entropy of its surname distribution, which is a measure of diversity. Relative to alternative measured used in the literature, surname entropy has both the advantage of reflecting very closely the population dynamics that drive social closure (in particular male immigration and marriage patterns) and that of being widely available at a very disaggregated level. The statistical association between surname entropy and crime and tax evasion rates is highly significant, relevant in magnitude and extremely robust (but for the cities subsample). After discussing and trying to rule out endogeneity, we conclude that our findings are likely to reflect a causal impact of social closure on crime and tax evasion rates.

Our results support the view that social closure favors limited as opposed to generalized morality, strengthening cooperation at the local level, but hampering cooperation with strangers (Banfield, 1958; Platteau, 2000; Tabellini, 2008). As mentioned in Section 1, there are several channels through which such effect may take place, including social enforcement and norm internalization. Our analysis suggests that both are at play.

On the one hand, in more closed communities social control may be higher and crimes may be deterred by high social sanctions, which are facilitated by repeated interaction (Durkheim, 1893; Posner, 1997; Allcott et al., 2007; Buonanno et al., 2009, 2012). For instance, stealing in a closed community entails a higher risk of being identified and sanctioned by other members. The analysis of crime rates by municipality size is coherent with this interpretation, as it shows that the crime-reducing effect of surname diversity is significant in villages and towns, but not in cities, where interaction is more anonymous. So part of the reduction in crime rates appears to depend on the fact that community closure raises the strength of social sanctions. Notice that social sanctions work as a deterrent of any crime that can be socially detected. Since this is the case both for property and violent crimes, we should expect to find a significant effect on each type of crime, and this is exactly what we find.

On the other hand, together and on top of the incentives created by social enforcement, more closed communities may facilitate the transmission and internalization of values of local cooperation, but not of cooperation with strangers.[21] This possibility is at the heart of the model by Tabellini (2008), where individuals have values of cooperation with neighbors but not necessarily with strangers. In that model, an improvement in social enforcement at the local level reduces the spread of values of cooperation with strangers. The reason is that it reduces the behavioral distance in local interactions between individuals with and without values of generalized cooperation: in daily interactions, which mostly take place with neighbors, they both act cooperatively due to the better social enforcement. If instilling values of generalized cooperation is costly, parents with such values will transmit them to their children only if this changes their behavior, whereas they will invest less in education to generalized morality if, as a result of better local enforcement, in daily interactions their children behave the same way with and without such values. We argued above that we can think of a higher social closure as an improvement in local enforcement. Then, according to the model by Tabellini (2008), we should expect that social closure is associated to higher cooperation at the local level, but to lower cooperation with strangers.[22] Our analysis of tax evasion is coherent with this view. Remember that paying TV taxes in Italy amounts to a private contribution to a national public good. In the case of TV tax evasion, peer monitoring is hard and public enforcement is extremely low everywhere, so it is easy to avoid any possible social or legal sanction. Yet, we find that surname diversity significantly reduces TV tax evasion rates. Such effect can hardly be attributed to social or public enforcement, and can rather be interpreted as due to the fact that more open communities facilitate the internalization of norms of generalized morality (in our case, norms of contribution to a national public good). Not surprisingly, the effect of social closure on TV tax evasion is significant in villages, where the frequency of interaction with neighbors reduces the incentive to transmit values of generalized morality, but not in towns and cities. This suggests that repeated interaction plays a central role in determining the effect of social closure on cooperative behavior also through value internalization and not only through social sanctions.

[21] One reason may be that, when interaction with strangers is less frequent, its benefits are less apparent, and distrust in strangers based on prior beliefs may persist, as there is little informational updating.

[22] Tabellini (2008) assumes paternalistic altruism, as in (Bisin and Verdier, 2001). One could alternatively imagine that perfectly altruistic parents transmit cooperative values to their tempted children as a commitment device, as in Cervellati and Vanin (2013), but our data does not allow measuring temptation in an adequate way, and even less relating it to social closure.

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Table 1: Summary statistics

Variables	Obs.	Mean	Std. dev.	Min	Max
Entropy	8,074	5.320	1.121	1.662	10.19
First share 93	8,076	5.231	4.649	0.238	53.62
First share 04	8,074	3.938	3.740	0.120	81.32
Total crime rate	8,076	27.10	19.41	0	914.4
Theft rate	8,076	12.61	11.25	0	459.2
Car theft rate	8,076	0.702	1.347	0	27.35
Burglary rate	8,076	2.095	2.031	0	34.93
Robbery rate	8,076	0.184	0.469	0	9.552
Serious assault rate	8,076	0.606	0.538	0	8.890
Tax evasion rate	8,076	33.78	10.96	0	93.40
Ruggedness	8,067	224.3	215.6	0.894	1,151
Mountain share	8,067	47.41	48.32	0	100
Altitude difference	8,067	0.659	0.654	0.00100	3.715
Altitude	8,067	0.548	0.497	0	3.072
Sea distance	8,067	0.0702	0.0557	0	0.230
Landlocked	8,067	0.921	0.270	0	1
Population	8,067	7.370	40.83	0.0337	2,679
Surface	8,067	37.28	49.98	0.660	1,308
Income	8,064	18.95	2.91	11.45	52.63
Share of males aged 0-14	8,064	6.776	1.452	0	13.41
Share of males aged 15-19	8,064	2.445	0.616	0	5.239
Share of males aged 20-24	8,064	2.638	0.609	0	5.160
Share of males aged 25-29	8,064	3.085	0.538	0	9.478
Share of males aged 30-34	8,064	3.673	0.592	0.826	7.651
Share of males aged 35-39	8,064	3.993	0.640	0.165	8.566
Share of males aged 40-44	8,064	4.021	0.573	0.522	7.101
Share of males aged 45-49	8,064	3.642	0.492	0.344	9.494
Share of males aged 50-54	8,064	3.340	0.491	0.723	8.936
Share of males aged 55-59	8,064	3.247	0.556	0.248	10.75
Share of males aged 60-64	8,064	2.860	0.572	0.842	8.606
Share of males aged 65 and more	8,064	9.353	2.787	1.719	32.62
Immigrant Male Share	8,064	2.440	2.040	0	14.87
Openness	8,064	6.469	2.447	1.212	24.55
Police	8,064	0.502	0.500	0	1
High school	8,064	22.70	4.788	3.289	48.28
Graduate	8,064	4.634	2.216	0	37.40

Table 2: Crime and surname diversity

DEPENDENT VARIABLES	Coefficient of *Entropy* in a regression of each dependent variable on *Entropy* and Controls								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Crime	6.912***	6.374***	6.164***	5.552***	5.912***	5.988***	5.117***	4.895***	4.851***
	[0.177]	[0.450]	[0.450]	[0.491]	[0.469]	[0.437]	[0.433]	[0.440]	[0.511]
Theft	4.797***	3.505***	3.365***	2.745***	2.858***	2.912***	2.834***	2.689***	2.556***
	[0.098]	[0.256]	[0.265]	[0.299]	[0.281]	[0.274]	[0.266]	[0.266]	[0.299]
Car Theft	0.518***	0.427***	0.401***	0.371***	0.371***	0.383***	0.385***	0.390***	0.349***
	[0.012]	[0.062]	[0.064]	[0.070]	[0.072]	[0.077]	[0.078]	[0.081]	[0.066]
Burglary	0.600***	0.199***	0.234***	0.079	0.084	0.103	0.162**	0.166**	0.142**
	[0.019]	[0.054]	[0.058]	[0.061]	[0.068]	[0.063]	[0.063]	[0.064]	[0.059]
Robbery	0.109***	0.091***	0.083***	0.082***	0.080***	0.086***	0.090***	0.096***	0.071***
	[0.004]	[0.020]	[0.020]	[0.024]	[0.024]	[0.027]	[0.028]	[0.033]	[0.012]
Serious Assault	0.198***	0.212***	0.211***	0.230***	0.224***	0.219***	0.190***	0.190***	0.199***
	[0.005]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]	[0.012]	[0.012]
CONTROLS									
Geography	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Migration	No	No	No	No	No	Yes	Yes	Yes	Yes
Police	No	No	No	No	No	No	Yes	Yes	Yes
Education	No	No	No	No	No	No	No	Yes	Yes
Province FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
SLL FE	No	No	No	No	No	No	No	No	Yes
Observations	8,074	8,067	8,067	8,064	8,064	8,064	8,064	8,064	8,064
N_clust	.	103	103	103	103	103	103	103	686

Notes: The top panel reports the coefficient of *Entropy*, estimated by Ordinary Least Squares (OLS) with municipality-level data, in a regression of each dependent variable (indicated on the left of the corresponding row) on *Entropy* and on the controls specified in the bottom panel in the corresponding column (each reported coefficient of *Entropy* corresponds to a different regression). Robust standard errors, clustered at the province level in columns (2) to (8) and at the SLL level in column (9), are presented in parentheses. *, ** and *** denote rejection of the null hypothesis of the coefficient being equal to 0 at 10%, 5% and 1% significance level, respectively.

Table 3: Crime and surname concentration

PANEL A	Coefficient of *First Share 04* in a regression of each dependent variable on *First Share 04* and Controls								
DEP. VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Crime	-1.130***	-0.830***	-0.776***	-0.583***	-0.561***	-0.488***	-0.305***	-0.271***	-0.329***
	[0.056]	[0.127]	[0.124]	[0.112]	[0.094]	[0.084]	[0.073]	[0.074]	[0.092]
Theft	-0.846***	-0.456***	-0.428***	-0.290***	-0.265***	-0.231***	-0.176***	-0.154***	-0.165***
	[0.032]	[0.071]	[0.070]	[0.063]	[0.053]	[0.049]	[0.044]	[0.046]	[0.045]
Car Theft	-0.085***	-0.042***	-0.039***	-0.027***	-0.019**	-0.017**	-0.010	-0.010	-0.011**
	[0.004]	[0.009]	[0.009]	[0.008]	[0.008]	[0.008]	[0.006]	[0.007]	[0.005]
Burglary	-0.132***	-0.035***	-0.036***	-0.014*	-0.012*	-0.007	-0.011*	-0.010*	-0.018**
	[0.006]	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]	[0.006]	[0.006]	[0.008]
Robbery	-0.017***	-0.007***	-0.006***	-0.004*	-0.002	-0.001	-0.000	-0.001	-0.001
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.001]
Serious assault	-0.036***	-0.029***	-0.027***	-0.025***	-0.020***	-0.018***	-0.011***	-0.011***	-0.012***
	[0.002]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]
Observations	8,076	8,069	8,069	8,069	8,069	8,069	8,069	8,069	8,069
N_clust	.	103	103	103	103	103	103	103	686
PANEL B	Coefficient of *First Share 93* in a regression of each dependent variable on *First Share 93* and Controls								
DEP. VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Crime	-1.059***	-0.788***	-0.744***	-0.584***	-0.568***	-0.511***	-0.348***	-0.316***	-0.351***
	[0.045]	[0.076]	[0.076]	[0.074]	[0.066]	[0.060]	[0.057]	[0.055]	[0.071]
Theft	-0.745***	-0.416***	-0.393***	-0.277***	-0.260***	-0.234***	-0.185***	-0.165***	-0.169***
	[0.026]	[0.046]	[0.046]	[0.048]	[0.044]	[0.042]	[0.040]	[0.040]	[0.040]
Car Theft	-0.070***	-0.037***	-0.034***	-0.024***	-0.018***	-0.017**	-0.011*	-0.010*	-0.011**
	[0.003]	[0.008]	[0.008]	[0.007]	[0.007]	[0.007]	[0.006]	[0.006]	[0.004]
Burglary	-0.115***	-0.038***	-0.039***	-0.020***	-0.020***	-0.016***	-0.020***	-0.020***	-0.024***
	[0.005]	[0.006]	[0.006]	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]
Robbery	-0.013***	-0.006***	-0.006**	-0.004*	-0.002	-0.002	-0.001	-0.002	-0.001
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.001]
Serious assault	-0.031***	-0.024***	-0.023***	-0.021***	-0.017***	-0.016***	-0.010***	-0.010***	-0.010***
	[0.001]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]
Observations	8,074	8,067	8,067	8,065	8,065	8,065	8,065	8,065	8,065
N_clust	.	103	103	103	103	103	103	103	686
CONTROLS									
Geography	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Migration	No	No	No	No	No	Yes	Yes	Yes	Yes
Police	No	No	No	No	No	No	Yes	Yes	Yes
Education	No	No	No	No	No	No	No	Yes	Yes
Province FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
SLL FE	No	No	No	No	No	No	No	No	Yes

Notes: This table has the same structure of Table 2, but panels A and B substitute *First Share 04* and *First Share 93* for *Entropy*, thus reporting their respective coefficient.

Table 4: Tax evasion and the distribution of surnames

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PANEL A: Coefficient of *Entropy*									
Entropy	-2.921***	-2.010***	-1.957***	-1.990***	-1.784***	-1.618***	-1.516***	-1.378***	-1.793***
	[0.104]	[0.293]	[0.317]	[0.359]	[0.335]	[0.333]	[0.352]	[0.391]	[0.225]
Observations	8,074	8,067	8,067	8,064	8,064	8,064	8,064	8,064	8,064
R-squared	0.0889	0.470	0.472	0.472	0.500	0.577	0.577	0.584	0.696
PANEL B: Coefficient of *First Share 04*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First Share 04	0.653***	0.261***	0.232***	0.198***	0.203***	0.261***	0.229***	0.205***	0.146***
	[0.032]	[0.052]	[0.054]	[0.053]	[0.062]	[0.062]	[0.067]	[0.063]	[0.050]
Observations	8,076	8,069	8,069	8,069	8,069	8,069	8,069	8,069	8,069
R-squared	0.0499	0.445	0.449	0.451	0.483	0.562	0.564	0.571	0.677
PANEL C: Coefficient of *First Share 93*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First Share 93	0.574***	0.273***	0.249***	0.222***	0.204***	0.256***	0.231***	0.207***	0.191***
	[0.026]	[0.051]	[0.051]	[0.049]	[0.045]	[0.042]	[0.042]	[0.042]	[0.031]
Observations	8,074	8,067	8,067	8,064	8,064	8,064	8,064	8,064	8,064
R-squared	0.0589	0.457	0.460	0.462	0.493	0.574	0.575	0.583	0.691
CONTROLS									
Geography	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Migration	No	No	No	No	No	Yes	Yes	Yes	Yes
Police	No	No	No	No	No	No	Yes	Yes	Yes
Education	No	No	No	No	No	No	No	Yes	Yes
Province FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
SLL FE	No	No	No	No	No	No	No	No	Yes
N_clust	.	103	103	103	103	103	103	103	686

Notes: This table is similar in structure to Tables 2 and 3, but Panels A, B and C report the coefficient of *Entropy*, *First Share 04* and *First Share 93*, respectively, estimated by Ordinary Least Squares (OLS), in a regression of the TV tax evasion rate on the corresponding explanatory variable and on the controls specified in the bottom panel.

Table 5: Crime and surname entropy: north-center-south subsamples

	(1) Total Crime	(2) Theft	(3) Car Theft	(4) Burglary	(5) Robbery	(6) Serious Assault	(7) Tax Evasion
PANEL A: NORTH							
Entropy	4.128***	2.057***	0.266***	0.127*	0.050***	0.188***	-2.244***
	[0.635]	[0.380]	[0.080]	[0.076]	[0.011]	[0.015]	[0.231]
Observations	4,516	4,516	4,516	4,516	4,516	4,516	4,516
N_clust	236	236	236	236	236	236	236
PANEL B: CENTER							
Entropy	5.300***	3.290***	0.523***	0.236*	0.080***	0.232***	-2.064***
	[1.180]	[0.686]	[0.159]	[0.133]	[0.013]	[0.045]	[0.442]
Observations	999	999	999	999	999	999	999
N_clust	133	133	133	133	133	133	133
PANEL C: SOUTH							
Entropy	3.891***	2.332***	0.532***	0.218***	0.074**	0.182***	-0.958
	[0.615]	[0.340]	[0.112]	[0.070]	[0.033]	[0.027]	[0.618]
Observations	2,549	2,549	2,549	2,549	2,549	2,549	2,549
N_clust	329	329	329	329	329	329	329
CONTROLS							
Geography	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migration	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SLL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table has a similar structure to Table 2 and of Table 4 (panel A), with the dependent variables presented by column and, as specified in the bottom panel, alwyas with the specification of column (9) of those tables. The specificity is that the first three panels of this table report separate estimates for the North, the Center and the South of Italy, respectively.

Table 6: Crime and surname entropy: village-town-city subsamples

	(1) Total Crime	(2) Theft	(3) Car Theft	(4) Burglary	(5) Robbery	(6) Serious Assault	(7) Tax Evasion
PANEL A: VILLAGES							
Entropy	4.880***	2.478***	0.082***	0.441***	0.016**	0.144***	-1.807***
	[0.685]	[0.387]	[0.031]	[0.064]	[0.007]	[0.020]	[0.271]
Observations	6,895	6,895	6,895	6,895	6,895	6,895	6,895
N_clust	666	666	666	666	666	666	666
PANEL B: TOWNS							
Entropy	8.375***	4.614***	0.936***	0.116	0.263**	0.180***	1.595
	[2.395]	[1.627]	[0.294]	[0.310]	[0.128]	[0.057]	[1.677]
Observations	1,022	1,022	1,022	1,022	1,022	1,022	1,022
N_clust	372	372	372	372	372	372	372
PANEL C: CITIES							
Entropy	13.051	9.283	0.429	-0.458	2.038***	-0.018	-0.406
	[22.027]	[7.014]	[1.847]	[1.304]	[0.768]	[0.460]	[6.910]
Observations	147	147	147	147	147	147	147
N_clust	114	114	114	114	114	114	114
CONTROLS							
Geography	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migration	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SLL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table has the same structure of Table 5, but the first three panels report separate estimates for villages (less than 10,000 inhabitants), towns (between 10,000 and 50,000 inhabitants) and cities (more than 50,000 inhabitants), respectively.

Table 7: Crime and surname entropy: spatial analysis

	(1) Total Crime	(2) Theft	(3) Car theft	(4) Burglary	(5) Robbery	(6) Serious Assault	(7) Tax Evasion
	Panel A: Spatial Autoregressive Model						
Entropy	4.864***	2.622***	0.349***	0.182***	0.071***	0.195***	-1.829***
	[0.328]	[0.175]	[0.016]	[0.029]	[0.005]	[0.009]	[0.120]
λ	0.003	0.001	0.052*	-0.025	0.028	0.001	0.001
	[0.018]	[0.020]	[0.028]	[0.019]	[0.037]	[0.021]	[0.005]
	Panel B: Spatial Error Model						
Entropy	4.875***	2.629***	0.349***	0.182***	0.071***	0.196***	-1.826***
	[0.328]	[0.175]	[0.016]	[0.029]	[0.005]	[0.009]	[0.120]
ρ	-0.161	-0.197	-0.384*	0.144	0.132	-0.389	-0.113
	[0.340]	[0.314]	[0.208]	[0.125]	[0.084]	[0.308]	[0.239]
	Panel C: Spatial Autoregressive and Error Model						
Entropy	4.875***	2.629***	0.350***	0.182***	0.071***	0.196***	-1.826***
	[0.328]	[0.174]	[0.016]	[0.029]	[0.005]	[0.009]	[0.120]
λ	-0.001	-0.004	0.047**	-0.025	0.057	0.005	-0.001
	[0.015]	[0.017]	[0.019]	[0.022]	[0.043]	[0.016]	[0.004]
ρ	-.160	-.204	-0.510**	0.113	0.155**	-0.402	-0.108
	[0.345]	[0.324]	[0.223]	[0.144]	[0.075]	[0.314]	[0.241]
CONTROLS							
Geography	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migration	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SLL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This Table presents the results of a spatial model estimated by means of the generalised spatial two stage least squares (GS2SLS) estimator of Kelejian and Prucha (1998). Included controls are the same as in the specification of column (9) of Table 2. The three panels report results from a spatial autoregressive model (panel A), a spatial error model (panel B) and a model with both spatial autoregressive and spatial error (panel C), estimated with an inverse geodesic distance matrix W. The dependent variable in each regression, which is the specific crime or tax evasion rate, are reported on the top of each column. Each panel displays the estimated coefficient of *Entropy* and of the spatial terms included in each model (λ and ρ are the coefficients of the spatial autoregressive and of the spatial error, respectively). Controls and SLL fixed effects are included in all specifications. Robust standard errors, clustered at the SLL level, are presented in parentheses. *, ** and *** denote rejection of the null hypothesis of the coefficient being equal to 0 at 10%, 5% and 1% significance level, respectively.

Table 8: Instrumental variables estimates

Panel A: First-stage							
Roman Roads Dummy				0.236***			
				[0.036]			
F-test				44.12			
Panel B: Second-stage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total Crime	Theft	Car Theft	Burglary	Robbery	Serious Assault	Tax Evasion
Entropy	13.966***	6.936***	1.029***	-0.411	0.218***	0.360***	-2.536**
	[2.601]	[1.439]	[0.170]	[0.272]	[0.056]	[0.073]	[1.096]
Observations	8,064	8,064	8,064	8,064	8,064	8,064	8,064
N_clust	686	686	686	686	686	686	686
Geography	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop&Surface	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Male Age Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migration	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SLL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table has a similar structure to Table 2 and of Table 4 (panel A), with the dependent variables presented by column and, as specified in the bottom part of Panel B, alwyas with the specification of column (9) of those tables. Panel B presents IV estimates, in which *Entropy* is instrumented with a dummy for the presence in a municipality of an ancient Roman road. Panel A reports the coefficient of the excluded instrument in the first stage regression, together with the F-test.

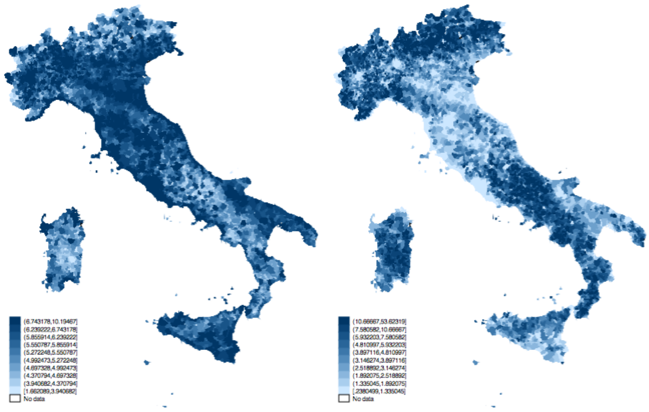

Figure 1: *Entropy* (left) and *First Share* (right) in 1993

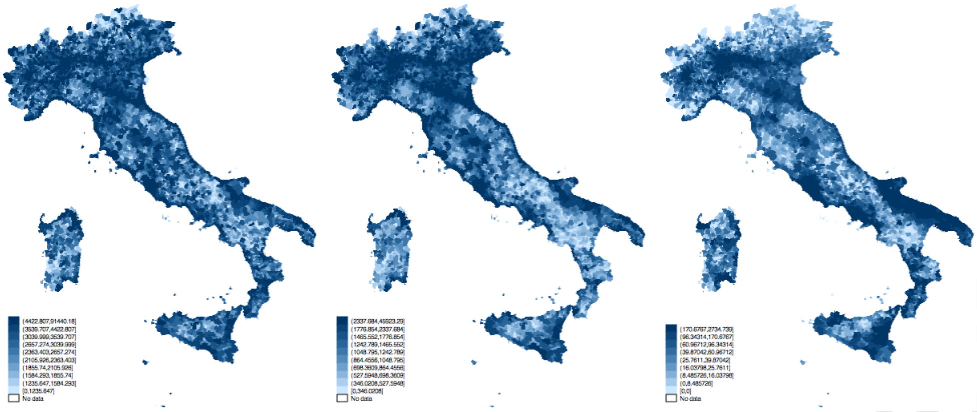

Figure 2: Total Crime (left), Theft (center), Car Theft (right)

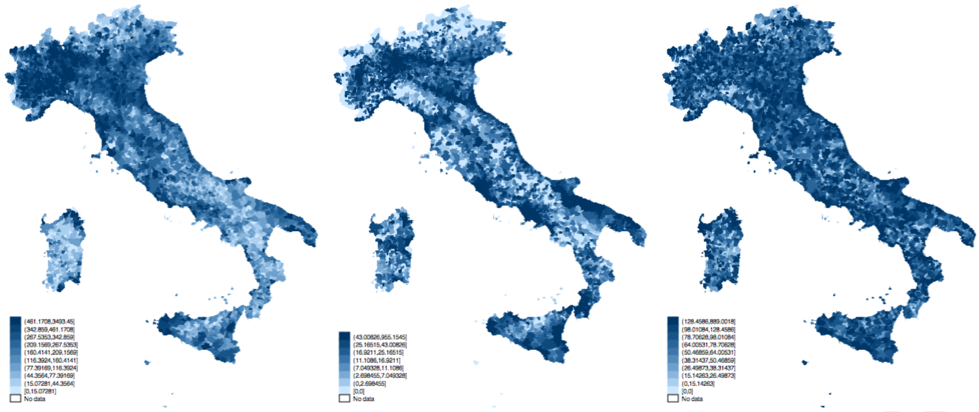

Figure 3: Burglary (left), Robbery (center), Serious Assault (right)

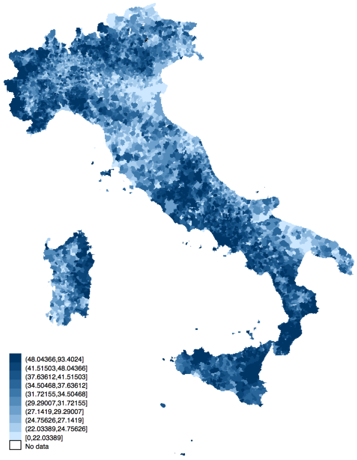

Figure 4: Tax evasion

Appendix

Table 9: Summary statistics by city size

VARIABLES	Villages Mean	Villages Std. dev	Towns Mean	Towns Std. dev	Cities Mean	Cities Std. dev
Entropy	5.051	0.923	6.765	0.727	7.899	0.872
First share 93	5.793	4.772	2.007	1.392	1.289	1.217
First share 04	4.367	3.861	1.468	1.033	1.020	1.076
Total crime rate	25.10	19.12	36.88	15.32	52.91	19.40
Theft rate	11.25	10.72	19.43	10.14	28.79	12.83
Car theft rate	0.452	0.901	1.965	2.015	3.662	3.248
Burglary rare	2.045	2.112	2.404	1.477	2.336	1.108
Robbery rate	0.122	0.287	0.501	0.915	0.906	0.998
Serious assault rate	0.543	0.525	0.942	0.454	1.227	0.415
Obs.	6,893		1,022		147	

Table 10: Crime and surname entropy: full specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Total Crime	Theft	Car Theft	Burglary	Robbery	Serious Assault	Tax Evasion
Entropy	4.851***	2.556***	0.349***	0.142**	0.071***	0.199***	-1.793***
	[0.511]	[0.299]	[0.066]	[0.059]	[0.012]	[0.012]	[0.225]
Ruggedness	-0.001	-0.003	-0.000	-0.002***	-0.000*	-0.000	0.005***
	[0.004]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]
Mountain share	-0.032***	-0.023***	-0.002***	-0.003***	-0.000***	-0.000*	-0.003
	[0.009]	[0.006]	[0.001]	[0.001]	[0.000]	[0.000]	[0.005]
Altitude difference	-6.256***	-2.374**	-0.130*	0.490***	-0.033	-0.066	-6.771***
	[1.756]	[1.004]	[0.071]	[0.166]	[0.026]	[0.051]	[0.779]
Altitude	11.006***	3.717**	0.151	-0.407	0.024	0.147*	16.033***
	[2.846]	[1.469]	[0.104]	[0.303]	[0.025]	[0.087]	[1.310]
Sea distance	-0.020	-0.014	-0.005	-0.004	-0.000	0.001	-0.001
	[0.034]	[0.021]	[0.003]	[0.004]	[0.001]	[0.001]	[0.020]
Landlocked	-10.988***	-6.896***	-0.249*	-0.854***	0.006	-0.273***	-4.159***
	[1.421]	[0.892]	[0.147]	[0.161]	[0.062]	[0.036]	[0.774]
Population	0.024*	0.017**	0.003***	-0.002***	0.001**	-0.000	0.006
	[0.013]	[0.007]	[0.001]	[0.001]	[0.000]	[0.000]	[0.007]
Surface	0.006	0.003	-0.000	0.001**	-0.000	0.000	0.006**
	[0.006]	[0.004]	[0.001]	[0.001]	[0.000]	[0.000]	[0.003]
Income	0.053	0.212**	-0.002	0.124***	-0.000	-0.012***	-0.079
	[0.161]	[0.089]	[0.009]	[0.025]	[0.003]	[0.005]	[0.081]
Immigrant Male Share	0.116	0.016	0.002	-0.019	0.002	0.020***	0.290***
	[0.154]	[0.084]	[0.009]	[0.025]	[0.004]	[0.005]	[0.092]
Openness	1.557***	0.685***	0.036***	0.162***	0.009*	0.015***	1.725***
	[0.184]	[0.109]	[0.010]	[0.025]	[0.006]	[0.005]	[0.092]
Police	3.295***	0.278	-0.041*	-0.209***	-0.027***	0.105***	-0.392*
	[0.436]	[0.208]	[0.021]	[0.041]	[0.007]	[0.014]	[0.203]
High school	0.188*	0.156***	0.003	0.006	-0.003	-0.002	-0.256***
	[0.100]	[0.054]	[0.005]	[0.012]	[0.003]	[0.003]	[0.046]
Graduate	0.200	0.061	0.008	-0.035*	0.007**	0.004	0.309***
	[0.148]	[0.087]	[0.010]	[0.019]	[0.003]	[0.005]	[0.076]
Male Age Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SLL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,064	8,064	8,064	8,064	8,064	8,064	8,064
N_clust	686	686	686	686	686	686	686
Adj. R-squared	0.277	0.390	0.649	0.503	0.658	0.317	0.696

Notes: OLS estimates. The dependent variable is indicated on top of each column. The specification of controls is the same as in column (9) of Table 2. Robust standard errors, clustered at the SLL level, are presented in parentheses. *, ** and *** denote rejection of the null hypothesis of the coefficient being equal to 0 at 10%, 5% and 1% significance level, respectively.