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# RESISTING TO THE EXTORTION RACKET: AN EMPIRICAL ANALYSIS

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# Resisting to the Extortion Racket: an Empirical Analysis

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**Abstract**

In this paper we perform a statistical evaluation of whether it is worthwhile, in economic terms, to resist to extortion demands by the mafia, from the point of view of firms operating in an area dominated by criminal organizations. We use a unique collected and matched database on firm characteristics on the city of Palermo, highly controlled by the mafia racket. The underlined idea is that the claimed resistance has (direct and indirect) costs and benefits, so that a rational firm should take this decision according its economic expectations on the future profits (in addition to potential ethic considerations). It means that the economic policy messages of this experience can be linked to make more profitable the racket resistance (as a signal sent to the market). Our evidences based on multilevel discrete choice models show that this decision is strongly influenced by socio-economic characteristics of the district, type of activity involved and other factors.

**Keywords** Organized Crime, Racketeering, Economic Growth, Discrete choice models.

**JEL classification** O17, K42, R11, C41

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# 1 Introduction

Extortion is a typical activity performed by criminal organizations such as the Sicilian Mafia (Gambetta , 1993, Konrad and Skaperdas , 1998, Varese , 2014, Balletta and Lavezzi , 2014). Extortion consists in the forced extraction of financial resources from firms, under the threat of punishment for those not complying. Some authors (see in particular Gambetta , 1993, Varese , 2014) have highlighted a distinction between the forced extraction of resources and the genuine payment for services that criminal organization can provide, as various forms of *protection*.[1]

Firms, however, may refuse to pay. This work aims at assessing the determinants of firms' behaviour with respect to extortion. In particular, we address the issue of the determinants of firms' resistance to extortion, in a context where such behaviour can be a way to build reputation and attract consumers. Starting from a unique dataset of firms from the city of Palermo, Sicily, that publicly signalled themselves as non payers or resistant to the extortion racket, we perform a statistical analysis to investigate the determinants of the decision to publicly declare to be a resistant. The firms we study are those that joined *Addiopizzo*, a Palermo-based NGO that, from 2004, invited firms declaring refusal to pay the local Mafia to join the NGO and become a member of a public list, aimed at addressing civic-minded consumers to buy their products or services.[2]

The steps we followed to construct the dataset are the following: i) we built a sample of 150 *Addiopizzo* firms; ii) the list of AP joiners (our study group) has been enriched by auxiliary information from Census data on Palermo districts. The linkage between the two sources has been done by a geographical matching by the address of the joiner and the Enumeration District database; iii) the new AP list has been matched with the CCIAA[3] data set of subscribers containing information on balance sheets;[4] iv) a stratified random

[1]Following Varese (2006, p. 412), we can list the following "services": "protection against extortion...; protection against theft and police harassment...; protection of thieves...; protection in relation to informally obtained credit and the retrieval of loans...; elimination of competitors...; intimidation of customers, workers, and trade unionists for the benefit of employers...; intimidation of lawful right-holders...; and the settlement of a variety of disputes...". See Varese (2006, p. 412) for references. In this perspective, extortion can be defined as: "the forced extraction of resources for services that are promised by not provided" (Varese , 2014, p. 344).

[2]Consumers wishing to signal their choice to support the *Addiopizzo* stores, may join a specific list, which is also publicly available.

[3]CCIAA is the acronym of the Italian Chamber of Commerce network. We extracted the data from the databank of CERVED, a private company that collects and organizes data from the CCIAA system.

[4]In Italy every legal firm must have a CCIAA position, and every joint stock company must deposit its balance sheets to the local CCIAA.

sample of active firms has been selected from the CCIAA positions of not AP-joiners (control group). The stratification criteria (see section 3 for details) balanced the control group by firm's age.

Our main results are:

1. Notwithstanding a quite similar production function estimation, the probability to be a joiner is more associated with younger and big (in terms of labour intensive factor) firms.

2. The stock of assets is negatively associated to the probability to join (as a measure of risk).

3. Finally, there is an effect related to the firm location, where we have a positive variance associated with the district level, partly explained by population and partly by human capital endowment (more educated district have higher joining rates).

The paper is organized as follows: in Section 2 we summarize the history of Addiopizzo together with a review of the relevant literature; in Section 3 we describe the dataset; Section 4 contains the empirical analysis: in particular Section 4.1 provides the descriptive statistics while Section 4.2 contains the econometric analysis; Section 5 contains concluding remarks and directions for further research.

# 2 The Addiopizzo experience and related literature

*Addiopizzo* (AP henceforth) means "farewell to pizzo", where *pizzo* is the Sicilian definition of the money extorted by the local Mafia, *Cosa Nostra*.[5] AP activity begun from an idea of few young activists who, in the night of June 29th, 2004, flooded the walls of Palermo with thousands of stickers carrying the slogan: *"A whole people who pays the pizzo is a people without dignity"*. This was a shocking message in a city where it is estimated that more than 80% of firms and stores pay the extortion racket (Confesercenti , 2010).

In 2005 the founders of AP organized a campaign to spread this message of resistance to the racket. In May 2006 a list of more than 100 businesses available to publicly denounce the *pizzo*, claiming their refusal to pay, was published in a local newspaper and diffusion on national media followed. In the years after 2004, more than 1000 firms have

[5]Thorough accounts of the Sicilian mafia are given, among others, by Gambetta (1993) and Paoli (2003).

been members of AP and at the time we collected the data (May 2012), the number of joiners was around 820. The list is publicly available.[6] Occasionally, AP runs campaigns targeted to firms of specific neighborhoods of Palermo, organizes meetings in schools, and holds a regular event in May, *"Fiera del consumo critico"*, in which AP firms present their products and various actitivities, from debates to live performances, take place.[7]

The idea of making public the list of joiners follows an economic insight. Consumers, in fact, are invited to shop at the AP stores if they wish to: "pay those who do not pay".[8] In other words, AP tries to elicit "critical consumption" by civic-minded citizens. AP stores clearly signal their membership by displaying an AP sticker at the entrance of their premises.

In this paper we try to answer the following question: why some firms join AP?[9] From the previous discussion, we can highlight two crucial aspects. The first one regards the characteristics of the firms and the expectation they have of the consequences of joining AP.[10] Which firms, therefore, are more likely to join? Does, for example, their size or their sector matter? As long as joining AP exposes firms to risks, then the amount of capital invested may influence the decision. The sector where the firm operates may play a role for example because some sectors are more heavily controlled by the Mafia, like Construction, or because the sector is a proxy for unobservable characteristics of firms' owners, which may be more or less inclined to resist to the Mafia. Firms' characteristics will be the first-level variables considered in the econometric analysis.

The second aspect regards the environment where the firm operates. In particular, the spread of anti-mafia values in the population is important, as purchases in AP stores can be considered as an anti-mafia act, under the assumption that shopping in non-AP stores would feed the Mafia through extorted resources. In this paper we control for the socio-economic characteristics of the geographical environment of the firm, i..e of the district where it is located, as second-level variables in the econometric analysis.

[6]See `http://www.addiopizzo.org`. A firm may leave the AP list for various reasons: going out of business, changes in ownership, with new owners asking to be cancelled, cancellation if interactions with organized crime are detected (see below).

[7]AP also supplies legal support in trials against the racketeers, mainly through the linked business association *Libero Futuro*, or psychological support to entrepreneurs considering to refuse to pay the Mafia. For more details, see Forno and Gunnarson (2010, pp. 109-111) and Gunnarsson (2014, pp.42-44).

[8]This is another slogan diffused by AP.

[9]This question echoes the question raised by Schelling (1971): why some firms' are victims of extortion? See Lavezzi (2008) for an empirical assessment.

[10]In a companion paper (Battisti et al. , 2014) we analyze the consequences for the economic performance for a firm joining AP.

Our paper is related to various strands of literature. First of all, to the literature on extortion implemented by organized crime. For example, Konrad and Skaperdas (1998) and Bueno de Mesquita and Hafer (2007) present theoretical models of extortion, Varese (2014) critically analyzes the distinction between extortion and protection, Asmundo and Lisciandra (2008) offer an empriical evaluation of the impact of extortion on regional GDP in Sicily, while Alexander (1997) and Balletta and Lavezzi (2014) combine a theoretical analyis with an emprirical analysis of extortion at firm level.[11] None of these articles, however, deal with the decision of the firms to resist the extortion racket.

Our work is also related to the literature on anti-mafia mobilization by the civil society. For example, Akerlof and Yellen (1994) focus on the "community" values that may influence the behaviour of citizens with respect to criminal gangs and the State;[12] Schneider and Schneider (2003) thoroughly analyze the case of Palermo, and reconstruct the history of the local antimafia movement and its evolution from the peasant movements of the fifties to the more recent, urban-based movements that developed in the eighties and the nineties, in particular after tragic events like the murders of journalist Giuseppe Impastato in 1978, Prefect Dalla Chiesa in 1982 or judges Falcone and Borsellino in 1992.[13] The recent experience of AP is read under a historical perspective by Forno and Gunnarson (2010) who note that, interestingly, AP did not follow sensational events like violent murders of key persons.[14] Finally, La Spina (2008) and Lavezzi (2014) read the AP experience in the perspective of a more general discussion of the possible anti-mafia strategies. All of these studies are, however, purely descriptive and, even if they are oriented to explain the anti-mafia behaviour, they do not offer an answer to the two above mentioned questions. In this work we propose a statistical model to estimate the probability of joining AP and to give evidence to answer to these questions.

Finally, our work is related to other scholarly works that specifically focus on AP. Partridge (2012) studied the choice to become "critical consumers" by a survey. The consumers surveyed are those that joined an AP consumers' list which can be consulted in the AP webpage. He finds that the respondents to the survey are in a high proportion in the age bracket 30-39, are likely to have a degree and to live in some of the central

[11]See also Lotspeich (1997) and Varese (2001) on extortion by the Russian Mafia.

[12]A similar point is made by Ramella and Trigilia (1997, p. 25)

[13]Jamieson (2000) analyzes in a broader perspective the antimafia reactions to the murders of 1992, also discussing the role of Italian politics, police forces and international actors.

[14]An early call for boycotting "Mafia business" was launched by the "Sheets committee", a movement mostly led by women, who appeared after assassination of judge Falcone, among the list of guidelines for citizens wishing to contrast the Mafia. The businesses mentioned were, however, those related to illegal trades like drugs and cigarettes. See Jamieson (2000, p. 131).

Palermo districts.[15] In addition, Partridge (2012) finds that the main determinants of the choice to be "critical consumers" are the willingness to support an organization led by young people, and to fight the Mafia by "everyday shoppping" (Forno and Gunnarson , 2010). The main limitation of this analysis is that, as the author recognizes, the lack of control for the self-selection of the respondents to the survey (and, we may add, for the self-selection of members of the sampled population to join the public AP list). Forno and Gunnarson (2010), instead, discuss the AP experience in the more general context of social mobilization and other form of critical consumption.

Some papers specifically focus on firms' choice to join AP. Vaccaro (2012) and Vaccaro and Palazzo (2014), adopting the perspective of business management, indirectly analyze such firms' decisions. Specifically, they study the behaviour of AP and how it contributed to the activation of the firms. They show that AP has been able to attract firms by strengthen its crediibility as an organization, in particular through the strategic disclosure of information about its own activities (e.g. on its budget) and on external activities (e.g. of Mafia), while Vaccaro and Palazzo (2014) emphasize the strategic use of values to elicit activation of firms and other agents such as consumers, students and members of the society at large.

Gunnarsson (2014), as we do in this paper, directly focuses on firms' decision to join AP. The sample and the methodology are, however, very different from ours: the sample is represented by the respondents to a survey, and does not include a control group and second-level variables. The variables considered in the research are also different from ours. In particular, Gunnarsson (2014) aims at assessing the role played by networks and trust. The networks analyzed are those involving AP firms but created by membership to associations different from AP (e.g. environmental, political, economic), or by family and other personal ties. Variables extracted from the survey are then used as regressors to explain the different *timing* of joining AP. Results show that early joiners are different from late joiners: their decision being based more strongly on membership to "action groups" and on family ties. Trust is instead found important for the decision of joiners that were not contacted by any member of their networks.

Finally, the recent paper by La Rosa et al. (2013) aims at studying the determinants of firms' decision to join AP adopting, as we do, a logistic regression approach. The main findings are that the leverage of firms and firms' size have a negative impact on the probability to join. Their sample is, however, very different: it is a self selected sample,

[15]These districts are Politeama, Liberta' and Resuttana-San Lorenzo. See Section 4.1 for a discussion of Palermo districts.

as ours, but it is not accompanied by a random control group. Our matching procedure allow us to have auxiliary variables at firm level (first level variables) and at district level (second level auxiliary variables). This provides us the information to separate the effect of individual factors from that of, say, environmental factors on the probability of joining AP.[16]

A caveat of the analysis of AP firms is that, even if with a very high probability they do not pay the *pizzo*, we are not able to control for the firms' truthful disclosure of information.[17] As discussed by Vaccaro (2012, p. 7), firms can be "double-game" players and choose to join an anti-racket organization to mask their actual connections with organized crime.[18] On the one hand, AP closely monitors the firms and has already expelled some "double-game" players.[19]. On the other hand, this is not relevant for this study because the observable declaration is anyway seen as a signal on the market, which may have positive consumption effects due to reputation (as a sort of customer discrimination in Becker , 1957), while acquiescence may avoid problems due to higher risks, that may be reflected for instance in indirect costs, such as higher interest rates, and direct costs, such as damages inflicted by the criminal organization. In other words we are forced to study the probability of declaring to have joined AP. This can be different from the probability of actual not payment of the Pizzo.

# 3 The Data

The dataset we built consists of two types of data: first-level data, i.e. firm-specific data and second-level data, i.e. data on the district where the firms are located. We have two groups of firms: firms that joined AP, and a control group of non-joiners. We only consider limited-liability firms, because they are the only type who must make their balance sheets public, by handing them in the Chambers of Commerce.

We obtained information on AP firms directly from *Addiopizzo*: this include qualitative information such as the sector, the location, and the date of joining AP.[20] We added

[16]La Rosa et al. (2013) also analyze the consequences on firms' economic performance of joining AP by comparing mean values of selected variables across the two groups or within the group of AP firms before and after joining. In Battisti et al. (2014) we study this issue with our sample, adopting a diff-in-diff strategy.

[17]When joining AP, firms must sign a declaration of non compliance with extortionary requests.

[18]Indeed, some evidence shows that mafia bosses may suggest to strategically join anti-mafia organizations for this purpose. See Vaccaro (2012, p. 7).

[19]Personal communication confirmed this.

[20]The date in which a firm joined AP is the only one not publicly available.

quantitative data from balance sheets of these firms from the CERVED dataset. The data on the districts are from the 2001 Census and, therefore, reflect the socio-economic conditions prior the creation of AP and should be exogenous with respect to the choice of joining AP.

The original dataset on AP firms has 839 entries, and refers to firms that joined within May 2012. The same firms may appear more than one if they have more branches. From the initial 839 entries we eliminate entries referred to firms outside of the province of Palermo (69) and entries related to branches.

The proportion among group 1. and 2. is given that 2. is three times bigger than 1. In order to build a database with the characteristics we needed to implement the econometric analysis relative to firms' choices in order to declare/not declare racket resistance we used:

- Information on joiners. Year, location, sector, address for 839 firms, 72% of whom within the municipality of Palermo. We got this information from AP: while the list of firms is public, the membership date had been kindly supplied from them.

- Census and geo-spatial data at sub-block level for the city of Palermo (3021 census cells and 25 districts) supplied from National Statistic Instituire ISTAT for the census 2001[21].

- Budget data from CCIAA for the years 2002-2011 (244 joiners and a control group of non-joiners of 732 randomly selected firms) as revenues, costs, cash, bank debts, data on employees and labour costs, assets, net patrimony and depreciation rates. For non limited liability firms (for those is not compulsory the delivery of budget data) we have just some basic information as number of employees and legal minimum requirement of patrimony to start the activity. These data are hystorically used to be delivered in paper form in Italy to the Chamber of Commerce System that is part of Statistical National System (SISTAN). Finally we bought these data from Cerved that is a private firm that collects and puts in electronic format.

- Toponomymic data in order to match data at point 2 to data at points 1, 3. These were supplied from the Municipality of Palermo, Department of Topography.

We started from the AP joiners group and with the addressess we match them to the census and district data through toponomymic information. Then we did the same for

[21]The census data are collected every 10 years. We decided to choose 2001 over 2011 in order to have choices of the firms based on territory characteristics already known when they decide to choose, in order to avoid simultaneity/endogeneity issues, given AP starts in 2005 and our sample is collected until 2012.

the random sample group. At the end we have firm data and district characteristics for joiners and non joiners.

At the time we collected this database it had 839 entries (actually, at the beginning of 2014 is 820 due to the natural turnover of new firms entered, old firms out of activity and so on). From the initial 839 entries we eliminate firms out of the province of Palermo (69) and collapse firms with local units that have repeated values for budget data. The joiners group is composed of 244 limited liability firms (190 within the municipality), close to 5% of the total number of firms for the city. Then with a small amount of information (number of workers, firm age, location) we have other 192 firms (individual and associations) from the province of Palermo and other 9 firms (the legal nature being uncertain). The control group has a proportion 3:1, so there are 732 limited liability and 576 other firms randomly selected.

Then we have some data for the remaining 112 firms of Palermo province without an identification number. It means that our working sample has 732+244=976 firms for whom we have all data sources. The budget data are, by construction, nominal data so we weight with the PCI of Palermo city, supplied from ISTAT, in order to make the variables in real terms. To summarize for every firm we will use in our econometric specification:

- firm budget real variables: revenues, costs, assets, employees, value added, cash, bank debt, depreciation.
- census/district variables: education, labour market, demography

Finally we averaged over the budget year available for every firm in order to avoid ciclicality and we end with a cross sectional database of 576 useful limited liability observations.

# 4 Empirical Analysis

## 4.1 Descriptive statistics

In this section we provide some descriptive statistics of the firms in our sample, in particular comparing the characteristics of the AP firms to those of the control sample, and of the territory of the city of Palermo, divided in 25 districts ("Quartieri").

Table 4.1 contains the evolution of the number of joiners in time.

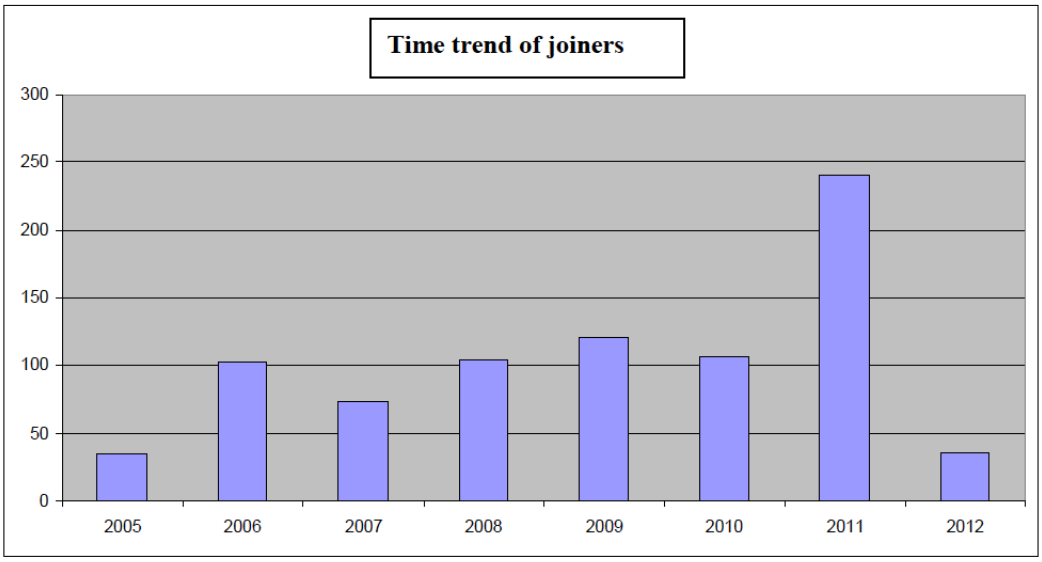


Figure 1: Number of joiners to *Addiopizzo* per year: 2005-2012

Comparing the joiners with the total data for the city we have that limited liability firms are strongly over represented in Addiopizzo sample.

### 4.1.1 First Level Variables

First of all, we compare the first-level variables AP and the control group. Table 1 contains average values and standard deviations for the firm-level data we considered, along with the p-value of a test on the difference of the means.

| | AP | | Control | | |
|---|---|---|---|---|---|
| | mean | std.dev | mean | std.dev | pval_toAv |
| Assets | 748178.32 | 4709943.16 | 615897.62 | 3380364.93 | 0.75 |
| Cash | 104130.05 | 480005.19 | 54933.47 | 175900.32 | 0.22 |
| Net Partimony | 374634.80 | 1707861.42 | 251391.39 | 1271324.14 | 0.42 |
| Profits | -2812.01 | 81004.82 | -20138.31 | 232021.24 | 0.16 |
| Debts | 463637.72 | 2652589.76 | 428064.21 | 2149966.68 | 0.88 |
| Revenues | 1477937.55 | 5086066.25 | 909457.68 | 3643809.14 | 0.21 |
| Personnel costs | 346859.69 | 1549325.66 | 122998.12 | 404548.88 | 0.08 |
| Returns | -27680.13 | 112590.88 | -22013.90 | 116237.65 | 0.59 |
| Gross Profits | 41947.74 | 178315.01 | 9915.70 | 169033.71 | 0.05 |
| Employers (classes) | 1.53 | 0.89 | 0.85 | 0.86 | 0.00 |
| Age of firm | 11.90 | 12.60 | 15.00 | 11.22 | 0.01 |

Table 1: Distribution across districts (SAMPLE A), non standardized data

Table 1 shows that AP firms have significantly higher levels of personnel costs, gross profits, number of workers, and a significantly lower firms' age. However, although the differences are not significant, AP firms seem to have higher levels of liquidity, of net wealth, of net profits, of revenues. In other words, they broadly appear are "healthier" firms.

Table 2 contains the distribution across sectors.[22]

| | num. firms | num. firms | perc. | perc. |
|---|---|---|---|---|
| Rental and Other Services | 10 | 38 | 6.67 | 7.92 |
| Education and Health | 7 | 36 | 4.67 | 7.50 |
| Arts, Sports, Entertainments | 10 | 7 | 6.67 | 1.46 |
| Manufacturing | 13 | 42 | 8.67 | 8.75 |
| Building | 13 | 82 | 8.67 | 17.08 |
| Trade and Repairing cars | 53 | 115 | 35.33 | 23.96 |
| Transport and Storage | 7 | 19 | 4.67 | 3.96 |
| Hotels and Restaurants | 12 | 21 | 8.00 | 4.38 |
| High Skill Services | 23 | 78 | 15.33 | 16.25 |
| Real Estate | 2 | 42 | 1.33 | 8.75 |

Table 2: Distribution across sectors, Ateco0b (< 1-digit), (SAMPLE A)

[22]The classification we consider in this paper is based on 10 sectors and is obtained by aggregating the 21 1-digit sectors represented in our sample. Table ??? contains the details of the classification.

Table 2 show that AP firms have a relatively higher share in the sectors of cultural activities, wholesale and retail trade, and hotels and restaurants. Firms in the control group instead appear relatively more frequently in the sectors of Construction and Real Estate Services.

Another preliminary investigation regards the economic differences of the two groups (joiners and not joiners) in terms of production functions. Let us estimate a simple Cobb-Douglas in non intensive form of the type:

$$Y_i = K_i^{\alpha} + L_i^{\delta} + \gamma_s + \phi_j + \epsilon_i. \tag{1}$$

on the cross section average sample of 572 firms. Where Y is given by the total revenue, while K is capital stock (total assets), L being a categorical discrete variable with 4 values, that are classes of employees with $\gamma$ as set of sectorial controls divided in 10 sectors, $\phi$ a geographical-administrative control given by the council (goes from 1 to 8)[23] and $\epsilon_i$ as white noise error term. With continuous data the exponents of L and K should sum up to one, divided in shares with two thirds for labour and one third for capital. Here we don't have a continuous variable for labour, but we just want to compare the coefficients, to look for structural differences among sets of observations.

| | AP sample | Non AP sample | Full sample | AP sample | Non AP sample | Full sample |
|---|---|---|---|---|---|---|
| Capital Stock | 0.325*** | 0.298*** | 0.302*** | 0.341*** | 0.265*** | 0.285*** |
| | (0.064) | (0.038) | (0.032) | (0.068) | (0.039) | (0.033) |
| Number of Workers | 0.739*** | 0.571*** | 0.609*** | 0.661*** | 0.598*** | 0.625*** |
| | (0.106) | (0.074) | (0.058) | (0.112) | (0.073) | (0.059) |
| Constant | 8.959*** | 8.869*** | 8.863*** | 8.008*** | 9.041*** | 8.765*** |
| | (0.722) | (0.437) | (0.364) | (0.666) | (0.405) | (0.342) |
| $R^2$ | 0.69 | 0.51 | 0.56 | 0.59 | 0.42 | 0.48 |
| Obs | 131 | 284 | 415 | 131 | 284 | 415 |
| Sectorial dummies | YES | YES | YES | NO | NO | NO |
| Test K coeff equal to full sample (p-val.) | 0.72 | 0.92 | | 0.40 | 0.62 | |
| Test L coeff equal to full sample (p-val.) | 0.22 | 0.61 | | 0.74 | 0.71 | |
| Test CRS (p-val.) | 0.46 | 0.04 | 0.07 | 0.98 | 0.04 | 0.08 |

Table 3: Dependent variable Total Revenues. Standard errors in parenthesis. ***,** ,* denote significant coefficients at 1%, 5% and 10%

The fits of the regressions is quite good, being a cross section sample, ranging from 0.45 to 0.69 and we see how the coefficients are quite close passing from one group to another. Results in table 5 show that there are not statistical differences of the two groups (the p-values of the tests are bigger than 0.10), respectively in columns labelled as AP and Non

[23] We also tried smaller level as district, with unchanged results.

AP with respect of the full sample in column 3 and that the exponent of capital is close to the textbook level one expects. It means we are not comparing different samples with respect to the fundamentals of productivity returns, in the view of a production function.

### 4.1.2 Second Level Variables

The second-level variables we consider characterize the district where the AP firms are located. Figure 2 offers a graphical representation of the distribution of AP firms in the 25 Palermo districts.[24]

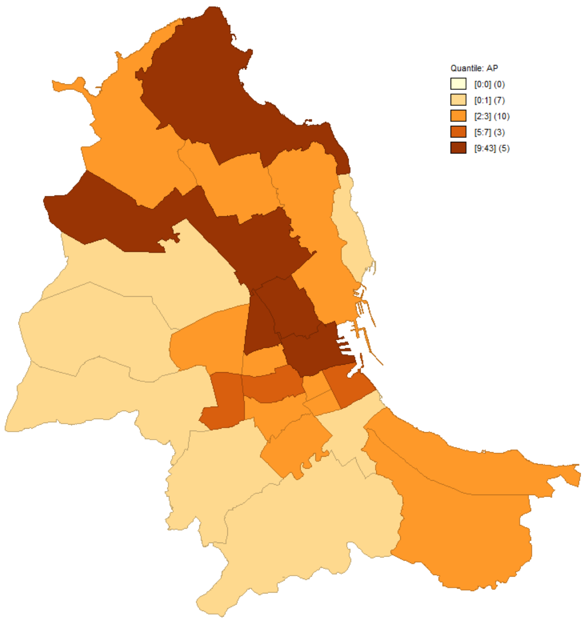


Figure 2: Distribution of AP firms in the 25 Palermo districts

Figure 2 shows that the distribution is not homogeneous in space. The districts featuring highest numbers of AP firms are located in the central-eastern part of the city: Politeama, Liberta', Malaspina-Palagonia, Resuttana-San Lorenzo and Partanna-Mondello. The number of AP firms is relatively higher than the number of firms in the control sample, which can be considered as a proxy of the density of economic activities present in the district, in the districts of Politeama and Partanna-Mondello.[25] There is, however, a vast area including many peripheral districts in which no AP firms are present.[26]

[24]Figure A in Appendix A contains a map of the Palermo districts and their names.

[25]See Table 5 in Appendix A.

[26]The contiguous dističts of: Cruillas CEP, Borgo Nuovo, Boccadifalco, Mezzomonreale, Villagrazia-Falsomiele, Oreto and the district of Arenella - Vergine Maria. Results are not affected by considering the largest sample, in which some districts have one or two AP firms instead of zero.

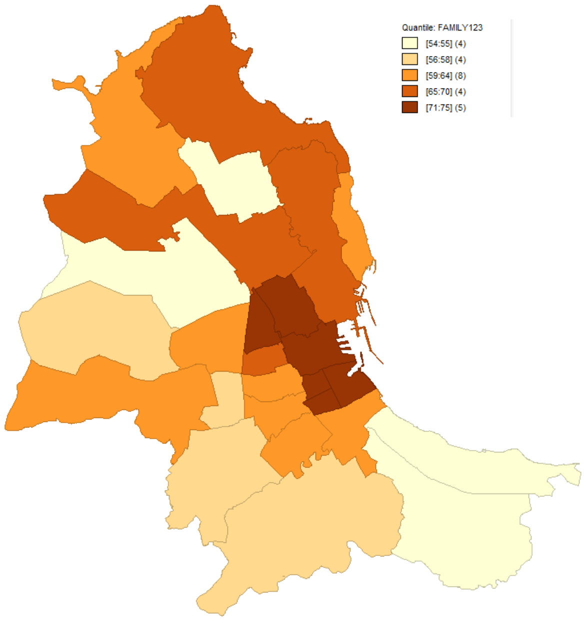


Figure 3: Shares of families with 1-3 members in the 25 Palermo districts

Figures 3, 4 and 5 present, respectively, information on the demographic characteristics of the districts, a proxy for human capital levels and unemployment rates.[27]

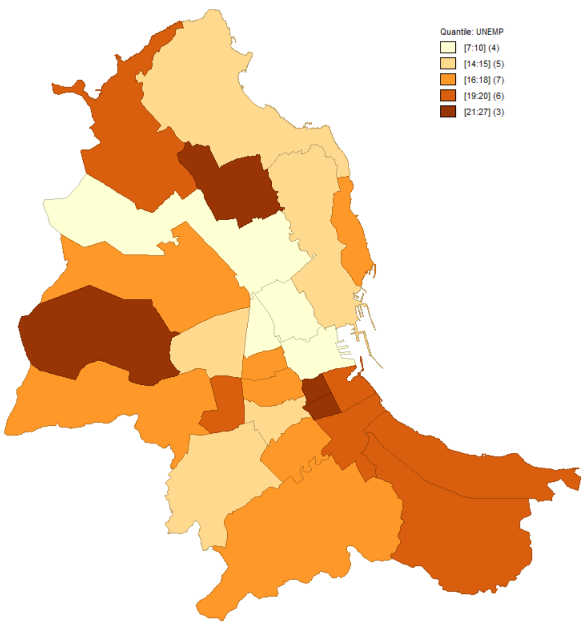


Figure 5: Unemployment rates in the 25 Palermo districts

Figure 3 highlights the presence of profound differences in the demographic structure

[27]Tables 8, 9 and 10 in Appendix A report these and other statistics.

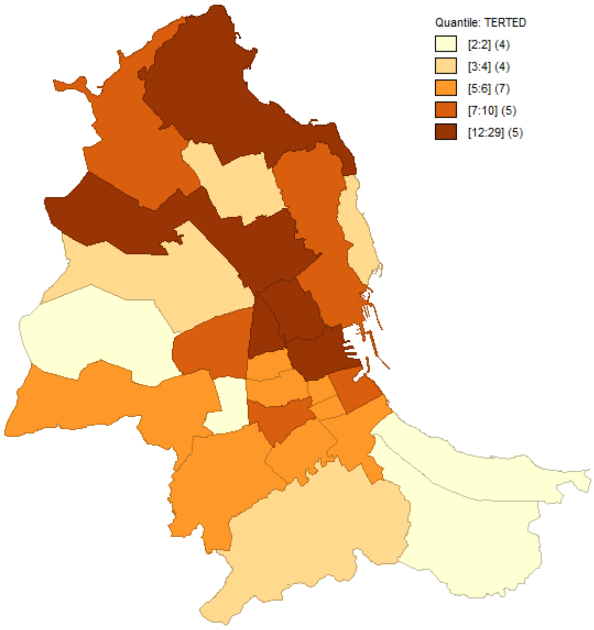


Figure 4: Shares of population with tertiary education in the 25 Palermo districts

across the districts. In the districts where AP firms are more numerous, the share of small families, i.e. with 1-3 members is approximately 70%, while in the districts with the lowest presence, the share is approximately 55%. This differences is reflected in the shares of large families (see Table 8) which is, respectively, approximately 7% and 15%. Table 8 also shows that the dependency ratios, i.e. the ratio of the share of population over 64 on the population under 14, is generally higher than 1 in the former and largely below 1 in the latter districts.

A similar, strongly divergent pattern is found when we observe human capital. Figure 4 shows that the districts with the highest presence of AP firms are relatively richer in human capital, measured by the share of population with tertiary education. This share is approximately 20%, while in the districts with little or no presence of AP firms this share is around 5% or less. Table 9 shows that in the latter districts, the largest majority of citizens completed primary education or have no education at all.

Perhaps not surprisingly, Figure 5 shows that unemployment rates are, respectively in the two groups of districts, around 10% and 17%, a pattern reflected by the employment rates (see Table 10) which amount to, approximately, 85% and 70%

Overall, the picture of Palermo is of a city in which two different socio-economic contexts co-exist: one in which population is educated, generally employed and lives in families of small size, and one in which population has little or no education, live in large families, and is characterized by high unemployment rates. Income data at district level are not available, but this picture suggests the coexistence in Palermo of rich and poor neigbhoroods, where the income differences are likely to be sizeable.

## 4.2 Econometric analysis

### 4.2.1 Methodology

Hierarchical or multilevel data are common in the social and behavioral sciences. In this paper, analysed data show a typical hierarchical structure (Bryk and Raudenbush, 2002; Snijders and Bosker, 2011) where lower-level units (individuals) are nested within higher-level units (clusters). Here, firms are clustered in neighborhoods and define a two-level hierarchical data structure. Because of this we can expect that firms located within each neighborhood, sharing the same unobserved factors, due to the exposure to common environmental or contextual effects, have correlated values of the response variable. When this occurs, analyzing lower-level units as if they were independent can produce biased standard errors of the regression coefficients, thus resulting in erroneous inferences (Hox, 2010) and possible substantive mistakes when interpreting the effects of predictor variables. Furthermore, in the analysis of such data, it is usually informative to take into account the sources of variability in the responses associated with each level of nesting, in this case the variance between firms and between neighborhoods, respectively.

Multilevel regression models (Goldstein, 2011; Raudenbush and Bryk, 2002; Sneijder and Bosker, 2011) are suitable for handling dependence among the responses resulting from a hierarchical data structure, also analysing the complex pattern of variability. In multilevel models, the total variance of the response variable is partitioned into its different components of variation, due to the various cluster levels in the data. The effect of clustering is modelled by introducing random effects (Laird and Ware, 1982), that is a continuous latent variable following a known parametric distribution, whose values are constant within clusters but vary across clusters. Independence across observations is assumed at cluster-level (neighborhood) whereas at individual-level (firms) it is assumed only among units belonging to different clusters (independence conditional on cluster membership). As a consequence, cluster-level random effects can be interpreted as the effects of neighborhood-levels unmeasured covariates that induce dependence among firms in the same neighborhood whereas indivudual-level random effects represent residuals specific to each firm after taking into account cluster effects. To explain at least some of the cluster-level variability, neighborhood-level covariates can also be introduced.

In the literature, multilevel regression models has become known under a variety of names, such as random coefficient model (de Leeuw and Kreft, 1986; Longford, 1987), variance component model (Longford, 1987), hierarchical linear model (Raudenbush and Bryk, 1986; 1988) and mixed models (McCulloch, Searle and Neuhaus, 2008). Although these models are not strictly the same, they can be referred collectively as "*multilevel regression models*" (Hox. 2010). Substantive literature treating multilevel models includes Bryk and Raudenbush (2002), Gelman and Hill (2007), Snijders and Bosker (2011) and Hox (2010) for excellent introduction and Longford (1993), Demidenko (2004), de Leeuw and Meijer (2008a) and Goldstein (2011) for more detailed mathematical background.

In this research, the response variable, indicated with y, is binary and distinguishes the firms that decided to associate with "Addiopizzo" by May, 2012 (y = 1) from the others (y = 0). The analysis is performed by using a two-level random intercepts logistic regression model (Goldstein, 2011; Rabe-Hesketh, Skrondal and Pickles, 2004). Given a binary outcome yij [0,1] observed on firm i, with i=1,2,..., $N_j$, located in neighborhood j, with j=1,2,..., G and being $P_{ij} = Pr(y_{ij} = 1)$ the probability that yij takes on the value of 1 (a firm associated with "Addiopizzo"), the model is defined in terms of the natural logarithm of the odds ratio (logit), indicated as $ln(P_{ij}/1 - P_{ij})$. Hence, the two-level random intercepts logistic regression model can be expressed as a linear function of the explanatory variables using the single equation mixed model formulation (Rabe-Hesketh, Skrondal and Pickles, 2004):

$$ln\left(\frac{P_{ij}}{1 - P_{ij}}\right) = \beta_0 + \beta_1 x_{ij} + \gamma w_{ij} + u_i \tag{2}$$

where $x_{ij}$ is a vector of predictors for firm i placed in neighborhood j and $w_j$ is a vector of predictors characterizing the neighborhood j. The random effects are given by the level 2 residual, $u_j$ $N(0, u)$, which define the effect of being in neighborhood j on the log-odds.

This parameter represent a continuous and unobservable quantity shared by the firms within a particular neighborhood that captures all the relevant factors not accounted for by the observed covariates. The magnitude of the standard deviation, u, indicates the strength of the influence of the specific neighborhood j on the log-odds. The fixed parameters to be estimated are $\beta_0$, $\beta_1$ and $\gamma$. More specifically, $\beta_0$ represents the population average log-odds when $x_{ij} = 0$ and $u_j = 0$; $\beta_1$ is the vector of the regression coefficients quantifying the effect on log-odds of a 1-unit increase in x for all the firms in the same neighborhood, thus having the same value of u; $\gamma$ is the vector of the regression coefficients for the predictors characterizing the neighborhood j. The probability of joining to "Addiopizzo" for firm $i$ in neighborhood $j$ is calculated as follows, for given values of the predictors $x_{ij}$, $w_j$ and $u_j$, the specific term:

$$P_{ij} = \frac{exp^{\beta_0+\beta_1 x_{ij}+\gamma w_{ij}+u_i}}{1+exp^{\beta_0+\beta_1 x_{ij}+\gamma w_{ij}+u_i}} \tag{3}$$

From the previous formula it is also possible to make predictions for "ideal" or "typical" firms having particular values for the vector of covariates, given the value of the random effect. The measurement of the extent to which the observations in a cluster are correlated is often of interest and can be expressed by the intraclass correlation coefficient (ICC), indicated with . This quantity can be obtained as the ratio of the variance of the random effects $u_j$ to the total variance and can be interpreted as the proportion of variance explained by clustering. Since the logistic distribution for the level-one residual implies a variance of $\pi^2/3$, the intraclass correlation in a two-level logistic random intercept model is defined as follows:

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \pi^2/3} \tag{4}$$

This formulation can be used also to express the residual intraclass correlation coefficient, that is the intraclass correlation after controlling for the effects of the explanatory variables. Methods for estimating hierarchical or multilevel logistic models are based on maximum likelihood (ML) (Demidenko, 2004; Skrondal and Rabe-Hesketh, 2004; Tuerlincks et al. 2006) or, alternatively, on Bayesian methods (Browne and Draper, 2000; Condgon, 2006; Draper, 2010).

When the second level effects are treated as random and the model parameters as fixed, inference is usually based on the marginal likelihood, that is the likelihood of data given the random effects, integrated over the random effects distribution. In this case, except for multilevel linear models, parameter estimation involves inevitably numerical methods and some kinds of approximation because the integrals do not have a closed-form solution (Pinheiro and Bates, 1995; Skrondal and Rabe-Hesketh, 2004); currently the most used algorithms for approximating the integral employed in the calculation of the log likelihood are the Laplace approximation and adaptive numerical quadrature. In contrast, when both the random effects and the model parameters are treated as random variables, a Bayesian approach is applied and inference is based on the posterior distribution, given the observed data. Bayesian methods use Markov chain Monte Carlo (MCMC) simulation methods for sampling from the posterior distribution and estimating parameters by their posteriors means (Gelfand and Smith 1990; Clayton, 1996).

In this paper, ML approach is employed and estimation of the model parameters is performed using the *melogit* procedure, implemented in the software Stata 13.0. The integral required to calculate the log-likelihood is approximated by using the mean-variance adaptive Gauss-Hermite quadrature (Skrondal and Rabe-Hesketh, 2004) with 20 points of integration. (with 20-point adaptive quadrature) Following this approach, the quadrature locations and weights for individual clusters are updated during the optimization process by using the posterior mean and the posterior standard deviation.

Prediction of random effects and expected responses is also often required. An extensive treatment of this topic is addressed by Skrondal and Rabe-Hesketh (2004; 2009). For prediction of random effects, three methods can be employed, empirical Bayes (EB), empirical Bayes modal (EBM) and estimation using maximum likelihood (ML). However, empirical Bayes prediction (Efron and Morris, 1973 and 1975; Morris, 1983; Maritz and Lwin, 1989; Carlin and Louis, 2000a and 2000b) is the most widely used method for assigning values to random effects. For this method, Skrondal and Rabe-Hesketh (2009) also discuss three different kinds of standard errors (the posterior standard deviation, the marginal prediction error standard deviation and the marginal sampling standard deviation). For prediction of expected responses, conditional expectations, population-averaged (or marginal) expectations and cluster-averaged (or posterior mean) expectations are considered. In a random-intercept logistic regression model, Skrondal and Rabe-Hesketh (2009) recommend using the population-averaged for predicting the response of a new unit and the cluster-averaged probability if the prediction is for an existing cluster.

### 4.2.2 Results

In this section we report the results obtained through the mixed effect logistic regressions, when we model a second level linked to the district characteristics.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Total Assets | -0.977* | -0.836* | -0.894* | -0.914* | -0.935** | -0.910* | -0.951** | -0.958** |
| | (0.515) | (0.488) | (0.468) | (0.474) | (0.470) | (0.468) | (0.467) | (0.469) |
| Personnel costs | 1.005** | 0.854** | 0.911** | 0.933** | 0.947** | 0.926** | 0.970** | 0.972** |
| | (0.465) | (0.432) | (0.397) | (0.402) | (0.400) | (0.397) | (0.398) | (0.399) |
| Firm age | -0.028** | -0.029** | -0.030*** | -0.030*** | -0.030*** | -0.030*** | -0.030*** | -0.030*** |
| | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Debt / revenues | 0.028 | 0.034 | 0.033 | 0.033 | 0.034 | 0.033 | 0.033 | 0.034 |
| | (0.029) | (0.029) | (0.028) | (0.028) | (0.029) | (0.028) | (0.028) | (0.028) |
| Revenues | -0.294 | -0.174 | | | | | | |
| | (0.268) | (0.233) | | | | | | |
| Net Profits | -0.070 | -0.019 | | | | | | |
| | (0.559) | (0.444) | | | | | | |
| Gross Profits | 0.480 | 0.335 | | | | | | |
| | (0.444) | (0.385) | | | | | | |
| Campaigns Dummy | -0.762 | -0.752 | | | | | | |
| | (0.628) | (0.612) | | | | | | |
| Employee class 1 | 0.922*** | 1.055*** | 1.056*** | 1.066*** | 1.048*** | 1.051*** | 1.030*** | 1.035*** |
| | (0.319) | (0.307) | (0.305) | (0.306) | (0.305) | (0.304) | (0.302) | (0.303) |
| Employee class 2 | 1.715*** | 1.841*** | 1.787*** | 1.803*** | 1.786*** | 1.792*** | 1.764*** | 1.764*** |
| | (0.390) | (0.369) | (0.361) | (0.361) | (0.360) | (0.358) | (0.354) | (0.361) |
| Constant | -2.031*** | -1.942*** | -1.949*** | -4.921*** | -1.089** | -3.363*** | -1.217*** | 0.181 |
| | (0.535) | (0.355) | (0.346) | (1.813) | (0.514) | (0.843) | (0.440) | (0.840) |
| District Variance | 0.613** | 0.584** | 0.538** | 0.485* | 0.416 | 0.391 | 0.000 | 0.201 |
| Second level variables | NO | NO | NO | YES | YES | YES | YES | YES |
| Population share | | | | | -18.501** | | -23.158*** | -22.933*** |
| | | | | | (9.402) | | (7.623) | (8.435) |
| Tertiary education share | | | | | | | 3.067** | |
| | | | | | | | (1.384) | |
| Primary education share | | | | | | | | -2.088* |
| | | | | | | | | (1.160) |
| Self Employees | | | | | | 7.067* | | |
| | | | | | | (3.713) | | |
| Small size household | | | | 4.509* | | | | |
| | | | | (2.667) | | | | |
| Sector dummies | YES | NO | NO | NO | NO | NO | NO | NO |
| Obs | 558 | 558 | 558 | 558 | 558 | 558 | 558 | 558 |
| AIC | 567.41 | 574.37 | 569.26 | 568.06 | 567.40 | 567.72 | 565.84 | 566.73 |
| MAIC | 588.41 | 586.37 | 577.26 | 577.06 | 576.40 | 576.72 | 575.84 | 576.73 |

Table 4: Mixed effect Logistic Regression on the Determinants to stay in AP. Standard errors in parenthesis. ***,** ,* denote significant coefficients at 1%, 5% and 10%

Table 4 reports these results, passing from a model without second level in column one, to alternative specifications of the second level in the other columns. For the first level standardized variables we have some clear messages: the probability to join is positively associated with the labour composition variables (wages and class of employees, for this second one at a growing rate) and negatively associated with the assets and firm's age, while either the revenues or the dummy that controls for campaigns adopted in specific districts of the city do not look significant in any specification. Among the sectors (results are available upon request) a higher probability to join is associated with sector 4 and with a significance close also to 10% sectors 7 and 9. The negative sign of assets could be interpretated with a risky measure of the investment, while the firm's age coefficient show that on average, younger firms are more willing to declare their racket resistance. On the other hand, firms with higher workforce are more likely to be joiners. Then, we observe how there is a positive variance associated with the local level given by the districts. We then, try to explain this, by looking to some district characteristics variables regarding demography, human capital and labour market (there are not income data from the census statistics) ranging from column 5 to column 8 (we don't show all tests for non significant variables). Our prior is, after the statistics presentation of the city characteristics that a higher membership to the NGO is more associated with more educated districts, where is easier to elicit the critical consumption behaviour. It means that the more populated and poorer (given the quantity/quality demographic trade-off we showed before) districts have, on average, less firms that join AP. We found, by using the selection criteria tests, that the demography matters, either as small family percentage, or as population district share (with opposite signs, as we stressed). Then, from this, labour market variables seem do not affect this model, while education has a positive impact for primary and tertiary completed education (even if the residual variance of column 8 disappears). The inclusion of this second level variables improve also a little bit the selection criteria Akaike and Modified Akaike, but most of all, it reduces the district variance.

# 5 Conclusions

This work used a new built database in order to assess the relevance of critical consumption considerations in order to show acquiescence or resistance to organized crime racket. Starting from the new unique experience of AddioPizzo, an NGO that tried to fight extortion through critical consumption behaviour we built a database of firm and social district characteristics for the city of Palermo in the period 2002-2012. This idea is linked to the research fields of social mobility, customer discrimination, organized crime and is a natural experiment to assess the role of human capital unconstrained with respect to the institutions, given that the formal institution in the same city have to be the same. Our results give a clear-cut picture of the situation, highlighting the dominant roles of economic risk (proxied by the physical capital assets a firm belongs) and to the social behaviour linked to the local expected reaction to the decision to show extortion resistance. This latter point is proved by the strong statistical evidence that younger firms, with more workforce, living in highly educated districts, have much higher probability to join. This paper is also part of an open agenda, aimed also to measure the economic results implied by this decision, that are the counterfactual gains or losses that firms decide to show this resistance, tend to experience.

# References


Akerlof, G., and J. Yellen, (1994) "Gang Behavior, Law Enforcement and Community Values", in Aaron, H.J, and T. E. Mann (Eds.), *Values and Public Policy*, Washington: Brookings Institution.

Alexander, B. (1997). The Rational Racketeer: Pasta Protection in Depression Era Chicago, ***The Journal of Law and Economics*** 40, 175-202.

Asmundo, A. & Lisciandra, M. (2008). The Cost of Protection Racket in Sicily, ***Global Crime*** 9, 221-240.

Balletta, L. & Lavezzi, A.M. (2014). Extortion, Firm's Size and the Sectoral Allocation of Capital", mimeo.

Battisti, M., Fioroni, T., Lavezzi, AM., Masserini, L. and M. Pratesi (2014), The Costs and Benefits of Resisting the Extortion Racket, in progress.

Becker, G. (1957). ***The Economics of Discrimination***. Chicago, University of Chicago Press.

Browne W.J, & Draper, D. (2000). Implementation and performance issues in the Bayesian and likelihood fitting of multilevel models. ***Computational Statistics***, **15**, 391-420.

Browne, W. J., & Draper, D. (2004). A comparison of Bayesian and likelihood methods for fitting multilevel models. Submitted. Downloadable from http://multilevel.ioe.ac.uk/team/materials/wbrssa.pdf.

Bueno de Mesquita, E. & C. Hafer (2007). Public Protection or Private Extortion?, ***Economics and Politics*** 20, 1-32.

Carlin, B. P. & Louis, T. A. (2000a). ***Bayes and Empirical Bayes Methods for Data Analysis***, 2nd edn. BocaRaton: Chapman and Hall-CRC.

Carlin, B. P. & Louis, T. A. (2000b.) Empirical Bayes: past, present and future. ***Journal of America Statistical Association***, **95**, 1286-1289.

Clayton, D. G. (1996). ***Generalized linear mixed models***. In: Gilks, W. R., Richardson, S., and Spiegelhalter, D. J. (eds), Markov chain Monte Carlo in practice. London: Chapman and Hall.

Confesercenti (2010). XI Rapporto di Sos Impresa ***"Le mani della criminalit sulle imprese"***. Confesercenti.

Congdon, P. (2006). ***Bayesian Models for Categorical Data***. John Wiley and Sons, New York.

De Leeuw, J., & Kreft, I. G. G. (1986). Random coefficient models for multilevel analysis. ***Journal of Educational Statistics***, **11**, 57-85.

De Leeuw, J. & Meijer, E. (eds) (2008) ***Handbook of Multilevel Analysis***. New York: Springer.

Demidenko, E. (2004). ***Mixed Models. Theory and Applications***. Hoboken, NJ: Wiley.

Draper, D. (2008). ***Bayesian multilevel analysis and MCMC***. In Handbook of Quantitative Multilevel Analysis (de Leeuw J., editor). New York: Springer

Efron, B., & Morris, C. (1973). Stein's estimation rule and its competitors - an empirical Bayes approach, ***Journal of the American Statistical Association***, **68**, 117-130.

Efron, B., & Morris, C. (1975). Data analysis using Stein's estimator and its generalizations, ***Journal of the American Statistical Association***, **70**, 311-319.

Forno, F. & Gunnarson, C. (2010) Everyday Shopping to Fight the Mafia in Italy, in M. Micheletti and A. McFarland (eds.) ***Creative Participation: Responsibility-taking in the Political World***, London: Paradigm Publisher

Gambetta, D. (1993), ***The Sicilian Mafia: the Business of Private Protection***, Harvard University Press.

Gelfand, A. & Smith, A. (1990). Sampling-based approaches to calculating marginal densities, ***Journal of the American Statistical Association*** **85**, 398-409.

Gelman, A., & Hill, J. (2007). ***Data Analysis Using Regression And Multilevel/Hierarchical Models***. Cambridge, UK: Cambridge University Press

Glaeser, E. & Resseger, M.G. & Tobio, K. (2008). Urban Inequality, ***NBER Working Paper Series*** WP 14419.

Goldstein, H.(2011). ***Multilevel Statistical Models***, Wiley, New York.

Gunnarson, C. Changing the Game: Addiopizzo?s Mobilisation against Racketeering in Palermo.

Hox, J.J.(2010). ***Multilevel Analysis: Techniques and Applications***. 2nd edition. New York: Routledge .

Jamieson, A. (2000). The Antimafia: Italy's fight against organized crime. London: Macmillan.

Konrad, K. A. & Skaperdas, S. (1998). Extortion, ***Economica*** 65, 461-477.

La Rosa, F., Paternostro, S, Picciotto, L. (2013), Determinants and Consquences of the Anti-Mafia Entrepreneurial Behavior: an Empirical Study on Southern Italian Small-Medium Enterprises, mimeo.

La Spina, A. (2008). Recent Anti-Mafia Strategies: the Italian Experience, in Siegel, D. and H. Nelen (eds.), ***Organized Crime: Culture, Markets and Policies***, Springer.

Laird, N. M. & Ware, J. H. (1982). Random-Effects Models for longitudinal Data, ***Biometrics***, **38**, 963-974.

Lavezzi, A. M. (2008). Economic Structure and Vulnerability to Organised Crime: Evidence from Sicily, ***Global Crime*** 9, 198-220.

Lavezzi, A. M. (2014). Organised crime and the economy: a framework for policy prescriptions, ***Global Crime***, 15(1-2), 164-190.

Longford, N.T. (1987). A fast scoring algorithm for maximum likelihood estimation in unbalanced mixed models with nested random effects, ***Biometrika***, **74**, 817-827.

Lotspeich, R. (1997). An Economic Analysis of Extortion in Russia, ***MOCT-MOST: Economic Policy in Transitional Economies***, **7**, 21-53.

Maritz, J. S. & Lwin, T. (1989). ***Empirical Bayes Methods***. London: Chapman and Hall.

McCulloch, C.E.& Searle, S.R.& Neuhaus, J.M. (2008). ***Generalized, Linear, and Mixed Models***. New York: Wiley.

Morris, C. (1983). Parametric empirical Bayes inference, theory and applications, ***Journal of the American Statistical Association***, **78**, 47-65.

Paoli, L. (2003). ***Mafia Brotherhoods. Organized Crime, Italian Style***, Oxford University Press.

Partridge, H. (2012). The Determinants of and Barriers to Critical Consumption: A Study of Addiopizzo, ***Modern Italy***, **17**(3).

Pinheiro, IC. & Bates, D.M. (1995). Approximations to the log-likelihood function in non-linear mixed-effects models, ***Journal of Computational and Graphical Statistics***, **4**, 12-35.

Rabe-Hesketh, S., & Skrondal, A. (2006). Multilevel modelling of complex survey data, ***Journal of the Royal Statistical Society, Series A***, **169**, 805-827 .

Ramella, F. and C. Trigilia (1997), "Associazionismo e mobilitazione contro la criminalità organizzata nel Mezzogiorno", in Violante, L. (ed.), *Mafia e società italiana. Rapporto 1997*, Laterza.

Raudenbush, S.W. & Bryk, A.S. (1986). A hierarchical model for studying school effects, ***Sociology of Education***, **59**, 1-17.

Raudenbush, S.W. & Bryk, A.S. (1988). Methodological advances in studying effects of schools and classrooms on student learning, ***Review of Research on Education***, **15**, 423-476.

Raudenbush, S.W. & Bryk, A.S. (2002). ***Hierarchical Linear Models***. Second Edition. Sage Publications, Thousand Oaks.

Schelling, T. C. (1971), "What is the Business of Organized Crime?", *Journal of Public Law* 20, 71-84. Reprinted in T. C. Schelling (1984), *Choice and Consequences*, Harvard University Press.

Schneider, J. C. & Schneider, P. T. (2003). ***Reversible Destiny. Mafia, Antimafia and the Struggle for Palermo***, University of California Press.

Skrondal, A. & Rabe-Hesketh, S. (2009). Prediction in multilevel generalised linear models, ***Journal of the Royal Statistical Society, Series A***, **172**(3), 659-687.

Snijders, T.A. & Bosker, R.(2011). ***Multilevel analysis. An introduction to basic and advanced multilevel modelling***. 2nd edition. Thousand Oaks, CA: Sage .

Tuerlinckx, F. & Rijmen, F. & Verbeke, G. & De Boeck, P. (2006). Statistical inference in generalized linear mixed models: A review, ***British Journal of Mathematical and Statistical Psychology***, **59**, 225-255.

Vaccaro, A. (2012). To pay or not to pay? Dynamic transparency and the fight against the mafia?s extortionists. Journal of business ethics, 106(1), 23-35.

Vaccaro, A., & Palazzo, G. (2014). Values Against Violence. Institutional Change in Societies Dominated by Organized Crime. Academy of Management Journal, amj-2012.

Varese, F. (2001). ***The Russian Mafia: Private Protection in a New Market Economy: Private Protection in a New Market Economy.*** Oxford University Press.

Varese, F. (2006). How Mafias Migrate: The Case of the'Ndrangheta in Northern Italy, ***Law and Society Review*** **40**, 411-444.

Varese, F. (2014). Protection and Extortion, ***Oxford Handbook of Organized Crime***, 343-58.

**Tables**

# A Second-level variables

In this appendix we present the statistics relative to the second-level variables. Figure A contains the map of the Palermo districts

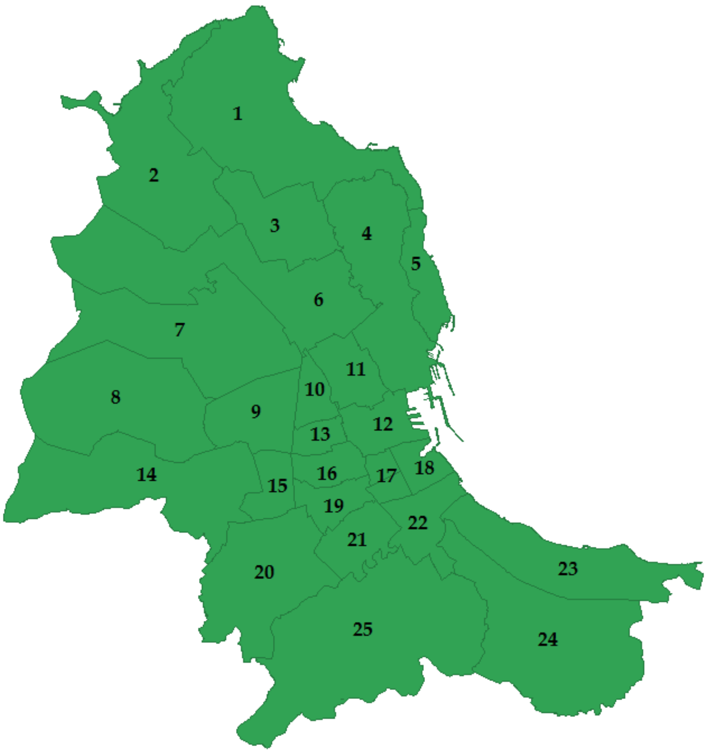


Table 5: Palermo districts: map

| ID | District name |
|---|---|
| 1 | Partanna Mondello |
| 2 | Tommaso Natale |
| 3 | Pallavicino |
| 4 | Monte Pellegrino |
| 5 | Arenella Vergine Maria |
| 6 | Resuttano San Lorenzo |
| 7 | Cruillas CEP |
| 8 | Borgo Nuovo |
| 9 | Uditore - Passo di Rigano |
| 10 | Malaspina-Palagonia |
| 11 | Liberta' |
| 12 | Politeama |
| 13 | Noce |
| 14 | Boccadifalco |
| 15 | Altarello |
| 16 | Zisa |
| 17 | Palazzo Reale - Monte di Pieta' |
| 18 | Tribunali-Castellammare |
| 19 | Cuba-Calatafimi |
| 20 | Mezzomonreale |
| 21 | Santa Rosalia |
| 22 | Oreto |
| 23 | Settecannoli |
| 24 | Brancaccio-Ciaculli |
| 25 | Villagrazia-Falsomiele |

Table 6: Palermo districts: names

Table 5 contains the distribution of the AP firms and the control group across the districts.

| | Circ | AP num. firms | Control n. firms | AP percent. | Control perc. |
|---|---|---|---|---|---|
| Tribunali-Castellammare | First | 5 | 18 | 3.33 | 3.73 |
| Palazzo Reale-Monte di Pieta' | First | 2 | 1 | 1.33 | 0.21 |
| Settecannoli | Second | 3 | 18 | 2.00 | 3.73 |
| Brancaccio-Ciaculli | Second | 2 | 7 | 1.33 | 1.45 |
| Oreto-Stazione | Third | 0 | 10 | 0.00 | 2.07 |
| Villagrazia-Falsomiele | Third | 1 | 9 | 0.67 | 1.86 |
| Cuba | Fourth | 3 | 12 | 2.00 | 2.48 |
| Mezzomonreale | Fourth | 0 | 19 | 0.00 | 3.93 |
| Altarello | Fourth | 6 | 5 | 4.00 | 1.04 |
| Santa Rosalia | Fourth | 2 | 3 | 1.33 | 0.62 |
| Boccadifalco | Fourth | 0 | 3 | 0.00 | 0.62 |
| Uditore-Passo di Rigano | Fifth | 3 | 19 | 2.00 | 3.93 |
| Zisa | Fifth | 7 | 10 | 4.67 | 2.07 |
| Noce | Fifth | 3 | 10 | 2.00 | 2.07 |
| Borgo Nuovo | Fifth | 0 | 4 | 0.00 | 0.83 |
| Resuttana-San Lorenzo | Sixth | 17 | 59 | 11.33 | 12.22 |
| Cruillas-S. Giov. Ap. (ex C.E.P.) | Sixth | 0 | 6 | 0.00 | 1.24 |
| Partanna Mondello | Seventh | 9 | 10 | 6.00 | 2.07 |
| Pallavicino | Seventh | 2 | 6 | 1.33 | 1.24 |
| Arenella-Vergine Maria | Seventh | 0 | 2 | 0.00 | 0.41 |
| Tommaso Natale | Seventh | 3 | 6 | 2.00 | 1.24 |
| Monte Pellegrino | Eighth | 3 | 24 | 2.00 | 4.97 |
| Politeama | Eighth | 43 | 114 | 28.67 | 23.60 |
| Liberta' | Eighth | 25 | 83 | 16.67 | 17.18 |
| Malaspina-Palagonia | Eighth | 11 | 25 | 7.33 | 5.18 |

Table 7: Distribution across districts (SAMPLE A)

Tables 8, 9 and 10 report the statitistic on selected demographic characteristics of the districts, of the levels of human capital and on labor market indicators, while Tables 11 and 11 contain the correlations among the variables.

| | Circ | Tot. Pop. | Depend. Ratio | Family 123 | Family 56 |
|---|---|---|---|---|---|
| Palazzo Reale-Monte di Pieta' | First | 11352 | 0.69 | 0.71 | 0.12 |
| Tribunali-Castellammare | First | 10137 | 0.86 | 0.73 | 0.12 |
| Brancaccio-Ciaculli | Second | 15618 | 0.45 | 0.54 | 0.18 |
| Settecannoli | Second | 52481 | 0.56 | 0.54 | 0.18 |
| Oreto-Stazione | Third | 42504 | 0.89 | 0.64 | 0.13 |
| Villagrazia-Falsomiele | Third | 40915 | 0.62 | 0.56 | 0.17 |
| Altarello | Fourth | 16944 | 0.53 | 0.57 | 0.15 |
| Boccadifalco | Fourth | 7909 | 0.47 | 0.59 | 0.16 |
| Cuba | Fourth | 23587 | 0.91 | 0.63 | 0.12 |
| Mezzomonreale | Fourth | 38567 | 0.7 | 0.58 | 0.14 |
| Santa Rosalia | Fourth | 25678 | 1.03 | 0.64 | 0.13 |
| Borgo Nuovo | Fifth | 21085 | 0.74 | 0.56 | 0.2 |
| Noce | Fifth | 29940 | 0.95 | 0.67 | 0.11 |
| Uditore-Passo di Rigano | Fifth | 33331 | 0.88 | 0.63 | 0.12 |
| Zisa | Fifth | 36260 | 0.89 | 0.63 | 0.13 |
| Cruillas-S. Giov. Ap. (ex C.E.P.) | Sixth | 32998 | 0.54 | 0.55 | 0.15 |
| Resuttana-San Lorenzo | Sixth | 45376 | 1.34 | 0.7 | 0.07 |
| Arenella-Vergine Maria | Seventh | 9299 | 0.64 | 0.59 | 0.15 |
| Pallavicino | Seventh | 27428 | 0.48 | 0.55 | 0.19 |
| Partanna Mondello | Seventh | 16652 | 0.77 | 0.68 | 0.09 |
| Tommaso Natale | Seventh | 21125 | 0.54 | 0.59 | 0.14 |
| Liberta' | Eighth | 45002 | 1.6 | 0.75 | 0.06 |
| Malaspina-Palagonia | Eighth | 21793 | 1.88 | 0.74 | 0.06 |
| Monte Pellegrino | Eighth | 29011 | 0.86 | 0.65 | 0.12 |
| Politeama | Eighth | 31730 | 1.18 | 0.73 | 0.08 |

Table 8: Demographic variables (districts). Tot.Pop.: total population; Depend. Ratio: dependency ratio (pop over 64 on pop under 14); Family 123: share of families with 1-3 components; Family 56: share of families with 5-6 components or more

| | Circ | Primm. Ed. | Prim. Ed. | Sec. Ed. | Tert. Ed. | Pop. Lit. | Pop. Illit. |
|---|---|---|---|---|---|---|---|
| Palazzo Reale-Monte di Pieta' | First | 0.32 | 0.61 | 0.11 | 0.05 | 0.17 | 0.06 |
| Tribunali-Castellammare | First | 0.27 | 0.54 | 0.16 | 0.1 | 0.16 | 0.05 |
| Brancaccio-Ciaculli | Second | 0.31 | 0.65 | 0.15 | 0.02 | 0.15 | 0.03 |
| Settecannoli | Second | 0.3 | 0.65 | 0.16 | 0.02 | 0.14 | 0.03 |
| Oreto-Stazione | Third | 0.29 | 0.61 | 0.2 | 0.05 | 0.12 | 0.03 |
| Villagrazia-Falsomiele | Third | 0.28 | 0.62 | 0.21 | 0.03 | 0.12 | 0.02 |
| Altarello | Fourth | 0.29 | 0.66 | 0.16 | 0.02 | 0.13 | 0.02 |
| Boccadifalco | Fourth | 0.23 | 0.58 | 0.21 | 0.06 | 0.12 | 0.02 |
| Cuba | Fourth | 0.24 | 0.55 | 0.26 | 0.07 | 0.1 | 0.02 |
| Mezzomonreale | Fourth | 0.22 | 0.56 | 0.28 | 0.06 | 0.09 | 0.01 |
| Santa Rosalia | Fourth | 0.28 | 0.61 | 0.2 | 0.05 | 0.11 | 0.03 |
| Borgo Nuovo | Fifth | 0.31 | 0.67 | 0.13 | 0.02 | 0.13 | 0.04 |
| Noce | Fifth | 0.27 | 0.59 | 0.21 | 0.06 | 0.11 | 0.02 |
| Uditore-Passo di Rigano | Fifth | 0.21 | 0.51 | 0.29 | 0.1 | 0.09 | 0.01 |
| Zisa | Fifth | 0.27 | 0.6 | 0.2 | 0.06 | 0.11 | 0.02 |
| Cruillas-S. Giov. Ap. (ex C.E.P.) | Sixth | 0.24 | 0.57 | 0.25 | 0.04 | 0.11 | 0.03 |
| Resuttana-San Lorenzo | Sixth | 0.13 | 0.34 | 0.39 | 0.2 | 0.06 | 0.01 |
| Arenella-Vergine Maria | Seventh | 0.29 | 0.64 | 0.19 | 0.03 | 0.12 | 0.01 |
| Pallavicino | Seventh | 0.31 | 0.63 | 0.15 | 0.04 | 0.14 | 0.03 |
| Partanna Mondello | Seventh | 0.2 | 0.47 | 0.3 | 0.12 | 0.09 | 0.01 |
| Tommaso Natale | Seventh | 0.22 | 0.56 | 0.25 | 0.07 | 0.11 | 0.02 |
| Liberta' | Eighth | 0.11 | 0.3 | 0.35 | 0.29 | 0.06 | 0 |
| Malaspina-Palagonia | Eighth | 0.14 | 0.34 | 0.37 | 0.23 | 0.06 | 0 |
| Monte Pellegrino | Eighth | 0.24 | 0.53 | 0.27 | 0.08 | 0.1 | 0.02 |
| Politeama | Eighth | 0.18 | 0.41 | 0.26 | 0.21 | 0.1 | 0.02 |

Table 9: Human Capital (districts). Primm. Ed.: share of population (age >6) with primary (elementary) education; Prim. Ed.: share of population (age >6) with primary (elementary and intermediate) education; Sec. Ed.: share of population (age >6) with secondary education; Tert. Ed.: share of population (age >6) with tertiary education; Pop. Lit.: share of population (age >6) with no education, literate; Pop. Illit.: share of population (age >6) with no education, illiterate

| | Circ | Empl. | Unempl. | Empl. Agr. | Empl. Manuf | Empl. Constr. | Empl. Serv. | Empl. Dep. | Empl. Indep. |
|---|---|---|---|---|---|---|---|---|---|
| Palazzo Reale-Monte di Pieta' | First | 0.54 | 0.27 | 0.02 | 0.09 | 0.07 | 0.82 | 0.83 | 0.16 |
| Tribunali-Castellammare | First | 0.68 | 0.19 | 0.03 | 0.1 | 0.05 | 0.81 | 0.76 | 0.23 |
| Brancaccio-Ciaculli | Second | 0.6 | 0.2 | 0.06 | 0.15 | 0.07 | 0.71 | 0.83 | 0.15 |
| Settecannoli | Second | 0.6 | 0.2 | 0.03 | 0.13 | 0.06 | 0.76 | 0.83 | 0.16 |
| Oreto-Stazione | Third | 0.65 | 0.19 | 0.02 | 0.12 | 0.06 | 0.79 | 0.83 | 0.15 |
| Villagrazia-Falsomiele | Third | 0.66 | 0.17 | 0.03 | 0.11 | 0.06 | 0.78 | 0.82 | 0.17 |
| Altarello | Fourth | 0.62 | 0.2 | 0.02 | 0.13 | 0.08 | 0.75 | 0.84 | 0.15 |
| Boccadifalco | Fourth | 0.65 | 0.16 | 0.01 | 0.1 | 0.09 | 0.78 | 0.81 | 0.17 |
| Cuba | Fourth | 0.72 | 0.15 | 0.02 | 0.09 | 0.04 | 0.83 | 0.83 | 0.16 |
| Mezzomonreale | Fourth | 0.72 | 0.14 | 0.02 | 0.09 | 0.05 | 0.83 | 0.82 | 0.17 |
| Santa Rosalia | Fourth | 0.64 | 0.18 | 0.02 | 0.09 | 0.05 | 0.83 | 0.85 | 0.14 |
| Borgo Nuovo | Fifth | 0.59 | 0.21 | 0.02 | 0.13 | 0.08 | 0.75 | 0.85 | 0.13 |
| Noce | Fifth | 0.67 | 0.17 | 0.02 | 0.1 | 0.06 | 0.81 | 0.82 | 0.17 |
| Uditore-Passo di Rigano | Fifth | 0.74 | 0.14 | 0.01 | 0.08 | 0.05 | 0.84 | 0.81 | 0.18 |
| Zisa | Fifth | 0.64 | 0.17 | 0.01 | 0.09 | 0.06 | 0.83 | 0.82 | 0.17 |
| illas-S. Giov. Ap. (ex C.E.P.) | Sixth | 0.68 | 0.18 | 0.02 | 0.11 | 0.07 | 0.79 | 0.83 | 0.16 |
| Resuttana-San Lorenzo | Sixth | 0.86 | 0.08 | 0.01 | 0.07 | 0.04 | 0.86 | 0.78 | 0.22 |
| Arenella-Vergine Maria | Seventh | 0.67 | 0.16 | 0.03 | 0.15 | 0.06 | 0.74 | 0.8 | 0.18 |
| Pallavicino | Seventh | 0.59 | 0.21 | 0.02 | 0.12 | 0.07 | 0.77 | 0.82 | 0.17 |
| Partanna Mondello | Seventh | 0.77 | 0.14 | 0.02 | 0.08 | 0.06 | 0.82 | 0.7 | 0.29 |
| Tommaso Natale | Seventh | 0.7 | 0.17 | 0.03 | 0.14 | 0.07 | 0.75 | 0.77 | 0.22 |
| Liberta' | Eighth | 0.87 | 0.07 | 0.01 | 0.05 | 0.03 | 0.89 | 0.75 | 0.25 |
| Malaspina-Palagonia | Eighth | 0.86 | 0.07 | 0.01 | 0.05 | 0.03 | 0.9 | 0.77 | 0.22 |
| Monte Pellegrino | Eighth | 0.73 | 0.15 | 0.01 | 0.12 | 0.05 | 0.8 | 0.81 | 0.18 |
| Politeama | Eighth | 0.82 | 0.1 | 0.02 | 0.07 | 0.04 | 0.87 | 0.73 | 0.26 |

Table 10: Labor Market indicators (districts). Empl.: employment rate; Unempl.: employment rate; Empl. Agr.: share of empl. in Agricolture; Empl. Manuf.: share of empl. in Manifacture; Empl. Constr.: share of empl. in Construction; Empl. Dep.: share of employees; Empl. Indep.: share of self-employed

|  | totPop | popShare | OldInd | fam123 | fam56 | popTertEd | popSecEd | popPrimEd | popPrimmEd | popLit | popIllit |
|---|---|---|---|---|---|---|---|---|---|---|---|
| totPop | 1 (0) | | | | | | | | | | |
| popShare | 1 (0) | 1 (0) | | | | | | | | | |
| oldInd | 0.29 (0.167) | 0.29 (0.167) | 1 (0) | | | | | | | | |
| fam123 | -0.02 (0.917) | -0.02 (0.917) | 0.8 (0) | 1 (0) | | | | | | | |
| fam56 | -0.12 (0.56) | -0.12 (0.56) | -0.82 (0) | -0.89 (0) | 1 (0) | | | | | | |
| opTertEd | 0.24 (0.25) | 0.24 (0.25) | 0.86 (0) | 0.8 (0) | -0.86 (0) | 1 (0) | | | | | |
| opSecEd | 0.36 (0.077) | 0.36 (0.077) | 0.7 (0) | 0.48 (0.015) | -0.77 (0) | 0.79 (0) | 1 (0) | | | | |
| pPrimEd | -0.26 (0.207) | -0.26 (0.207) | -0.84 (0) | -0.76 (0) | 0.88 (0) | -0.98 (0) | -0.88 (0) | 1 (0) | | | |
| PrimmEd | -0.27 (0.195) | -0.27 (0.195) | -0.74 (0) | -0.61 (0.001) | 0.82 (0) | -0.91 (0) | -0.95 (0) | 0.96 (0) | 1 (0) | | |
| popLit | -0.42 (0.035) | -0.42 (0.035) | -0.73 (0) | -0.42 (0.037) | 0.73 (0) | -0.74 (0) | -0.96 (0) | 0.81 (0) | 0.89 (0) | 1 (0) | |
| popIllit | -0.34 (0.097) | -0.34 (0.097) | -0.47 (0.017) | -0.15 (0.479) | 0.52 (0.008) | -0.56 (0.004) | -0.85 (0) | 0.62 (0.001) | 0.75 (0) | 0.89 (0) | 1 (0) |
| emp | 0.29 (0.163) | 0.29 (0.163) | 0.77 (0) | 0.62 (0.001) | -0.84 (0) | 0.9 (0) | 0.95 (0) | -0.94 (0) | -0.96 (0) | -0.91 (0) | -0.8 (0) |
| unemp | -0.34 (0.102) | -0.34 (0.102) | -0.75 (0) | -0.5 (0.011) | 0.74 (0) | -0.84 (0) | -0.93 (0) | 0.87 (0) | 0.92 (0) | 0.93 (0) | 0.88 (0) |
| empAgri | -0.13 (0.532) | -0.13 (0.532) | -0.48 (0.016) | -0.43 (0.03) | 0.52 (0.008) | -0.41 (0.043) | -0.5 (0.01) | 0.45 (0.023) | 0.5 (0.01) | 0.54 (0.005) | 0.29 (0.155) |
| empManu | -0.25 (0.223) | -0.25 (0.223) | -0.79 (0) | -0.76 (0) | 0.8 (0) | -0.8 (0) | -0.69 (0) | 0.82 (0) | 0.77 (0) | 0.66 (0) | 0.38 (0.057) |
| empBuil | -0.46 (0.021) | -0.46 (0.021) | -0.86 (0) | -0.7 (0) | 0.76 (0) | -0.76 (0) | -0.68 (0) | 0.76 (0) | 0.66 (0) | 0.68 (0) | 0.46 (0.021) |
| empServ | 0.32 (0.119) | 0.32 (0.119) | 0.86 (0) | 0.81 (0) | -0.86 (0) | 0.83 (0) | 0.73 (0) | -0.84 (0) | -0.78 (0) | -0.71 (0) | -0.41 (0.041) |
| mpIndep | -0.03 (0.901) | -0.03 (0.901) | 0.47 (0.018) | 0.66 (0) | -0.7 (0) | 0.77 (0) | 0.6 (0.002) | -0.76 (0) | -0.72 (0) | -0.5 (0.012) | -0.43 (0.031) |
| empDep | 0.05 (0.803) | 0.05 (0.803) | -0.43 (0.031) | -0.63 (0.001) | 0.66 (0) | -0.74 (0) | -0.57 (0.003) | 0.73 (0) | 0.69 (0) | 0.48 (0.016) | 0.43 (0.033) |
| usNoWat | -0.28 (0.18) | -0.28 (0.18) | -0.19 (0.372) | 0.03 (0.876) | -0.03 (0.892) | 0 (0.998) | -0.17 (0.418) | 0.06 (0.784) | 0.07 (0.75) | 0.17 (0.415) | 0.12 (0.563) |
| oodBuild | 0.24 (0.253) | 0.24 (0.253) | 0.08 (0.72) | -0.24 (0.246) | -0.04 (0.852) | 0.25 (0.227) | 0.5 (0.012) | -0.28 (0.176) | -0.44 (0.027) | -0.57 (0.003) | -0.71 (0) |

Table 11: Correlations among census indicators

| | emp | unemp | empAgri | empManu | empBuild | empServ | empIndip | empDip | housNoWat | goodBuild |
|---|---|---|---|---|---|---|---|---|---|---|
| emp | 1 (0) | | | | | | | | | |
| unemp | -0.97 (0) | 1 (0) | | | | | | | | |
| empAgri | -0.41 (0.043) | 0.4 (0.047) | 1 (0) | | | | | | | |
| npManu | -0.71 (0) | 0.67 (0) | 0.66 (0) | 1 (0) | | | | | | |
| npBuild | -0.76 (0) | 0.73 (0) | 0.29 (0.161) | 0.71 (0) | 1 (0) | | | | | |
| empServ | 0.76 (0) | -0.71 (0) | -0.69 (0) | -0.97 (0) | -0.82 (0) | 1 (0) | | | | |
| npIndep | 0.73 (0) | -0.63 (0.001) | -0.15 (0.47) | -0.53 (0.006) | -0.44 (0.028) | 0.51 (0.008) | 1 (0) | | | |
| empDep | -0.71 (0) | 0.61 (0.001) | 0.12 (0.577) | 0.48 (0.014) | 0.4 (0.049) | -0.46 (0.02) | -1 (0) | 1 (0) | | |
| sNoWat | -0.07 (0.754) | 0.15 (0.487) | 0.13 (0.532) | 0.28 (0.173) | 0.18 (0.395) | -0.22 (0.298) | 0.23 (0.274) | -0.24 (0.242) | 1 (0) | |
| odBuild | 0.43 (0.031) | -0.52 (0.007) | -0.07 (0.725) | -0.09 (0.654) | 0.01 (0.98) | 0.03 (0.869) | 0.33 (0.11) | -0.35 (0.084) | -0.1 (0.65) | 1 (0) |

Table 12: Correlations among census indicators