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The Economics of Extortion: Theory and Evidence on the Sicilian Mafia

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Luigi Balletta† Andrea Mario Lavezzi‡

March 26, 2019

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1 Introduction

Several countries around the world are plagued by the presence of organized crime. This phenomenon appears particularly widespread in some countries from Latin America, the former Soviet bloc, and East Asia (Van Dijk, 2007). Among European countries, Italy stands out as a peculiar case, as some regions of the South, namely Sicily, Calabria, Campania and Apulia feature the presence of powerful *Mafias* which still pose a serious threat to their development (see Paoli, 2003, for an introduction to the Italian case). For example, Pinotti (2015) estimates that, in the case of Apulia, the criminal organizations caused a reduction of regional GDP up to 16%. One of the Mafia activities affecting the legal economy is extortion, i.e. the forced extraction of resources from firms operating in legitimate sectors, under the threat of punishment for non compliance.

In this paper we provide a theoretical and empirical analysis of extortion based on a unique dataset of first-quality data on the exact amounts of *pizzo*[1] paid by a sample of Sicilian firms, matched to data from their financial statements. Our aim is to understand how Mafia sets the amount of money that firms are forced to pay on the basis of some firms' characteristics, namely size, and how this relationship varies by sector. In particular, we identify the stylized facts of the relationship between *pizzo* and firm's size and sector and then show that they can be accounted for by a principal-agent model in which the criminal organization cannot perfectly observe firms' productivity. The main empirical implication of our model, which we test using our dataset, is a concave relationship between firms' size and the amount of *pizzo* paid.

Our main findings are the following. The log of *pizzo* moderately increases with the log of firms' size: the estimated elasticity of *pizzo* with respect to firms' size is approximately 0.1, which implies a strongly concave relationship between *pizzo* and firms' size, characterized by marginal and average *pizzo* decreasing with size. The elasticities vary by sector of firm's activity: in some sectors such as Construction and Transports the estimated elasticity is higher than the average, taking on values of approximately 0.3. These elasticities show that "Mafia taxation" is highly *regressive*. The quantitative effect of varying firms' size on average *pizzo* is striking. We find that the average "*pizzo* rate", i.e. the percentage of operating profits appropriated by the Mafia, amounts to approximately 40% for small firms and decreases to approximately 2% for large firms.

These findings suggest specific microeconomic channels through which organized crime negatively affects economic growth: i) by erecting barriers to entry, ii) by stifling small firms

[1] *Pizzo* is the Sicilian definition of the money extorted by the Mafia.

which, in an environment where access to credit can be difficult because of crime itself, have little resources to expand,[2] and thus iii) by creating the conditions for a poverty trap based on non-convexity in the cost function.[3]

Our work is strongly influenced by the seminal contribution of Schelling (1971) on the economics of organized crime. Specifically, he identifies the characteristics that make a firm more vulnerable to the extortion racket. Firms of small size can be easier targets than large corporations as in the former it is easier for the mobster to force the owner to pay. In large firms, on the contrary, a *mafioso* should wander among floors of offices before eventually find somebody to threat. In addition, he points out that firms with more observable profits or revenues can be easier targets of the racket because it would be difficult for such firms to claim their incapacity to meet the extortionary requests. On the basis of these remarks, we chose to focus on firms' size and sector when analyzing extortion. However, in this paper we do not study the choice to extort or not extort a specific firm, but rather, given that a firm is extorted, the choice of the amount the Mafia demands given size and sector.

Recent works on the economics of organized crime include studies on the origins of the Mafia, emphasizing the role of land fragmentation (Bandiera, 2003), the presence of sulphur mines (Buonanno et al., 2015), of citrus fruits (Dimico et al., 2017), or of socialist movements that induced the landlords to resort to the Mafia for their repression (Acemoglu et el., 2017). Other economic analyses include Pinotti (2015) on the impact of mafias on economic growth, Barone and Narciso (2015) on the capacity of mafias to grab public funds, Buonanno et al. (2016) and Alesina et al. (2018) on the interactions between criminal organizations and politics, Buonanno and Pazzona (2014) on the diffusion of mafias in new territories, and Mastrobuoni and Patacchini (2012) on the internal structure of criminal organizations.

In the economic analysis of extortion, Konrad and Skaperdas (1998) propose a model of extortion in which costly investment in destructive capacity and asymmetric information about firm's value cause the emergence of conflict between the criminal organization and the extorted firm, leading to inefficient destruction of property. In our model, the criminal organization is strong enough to impose compliance on firms that open for business, thus conflict does not arise. On the other hand, we allow the criminal organization to condition the amount of money exorted on observable characteristics correlated with private information (namely, size), thus incentive compatibility induces distortion in productive choices and

[2]Analysing Italian regions, Bonaccorsi di Patti (2009) finds that the presence of organized crime in a region increases interest rates paid by firms on loans by approximately 30 basis points.

[3]Previous literature (e. g. Gambetta, 1993) has emphasized that organized crime creates local monopolies.

possibly exclusion from the market.

Aleksander (1997) studies the extortion racket in the Depression Era Chicago, where the local Mafia imposed a payment on pasta producers taking the form of a two-part tariff. Exploiting information on the tariff and on the local market conditions, she finds that Mafia "taxation" was regressive, as the highest burden from extortion was imposed on firms producing at smaller scales, a result similar to ours. She concludes that the organizational form of the pasta market was of a cartel, in which the criminal organization acted as enforcer (see Gambetta and Reuter, 1995, for a discussion of Mafia cartels).

Olken and Barron (2009) analyze extortion imposed by officers on truck drivers at check-points and weigh stations in Indonesia. They propose a theoretical model of price discrimination and test it on a sample of payments collected at check-points and weigh stations along two Indonesian routes. They show that market structure (measured by the number of check points) influences the payment structure, and that officers practice price discrimination. Our work shares with theirs the use of actual data on extortion. However, the kind of extortion analyzed by Olken and Barron (2009) refers to officers and should be more correctly classified as corruption.[4] Criminal organizations in the case studied by Olken and Barron (2009) can provide protection to truck drivers along the route against the payment of a quasi-fixed fee. Differently, in our study the focus is on extortion imposed by organized crime, who can price-discriminate among firms according to observable characteristics, such as size.[5]

Finally, Asmundo and Lisciandra (2008) estimate the size of overall revenues from extortion in Sicily using the dataset on *pizzo* payments that we use in this paper. In this paper, however, that dataset is expanded by data from firms' financial statements and, to the best of our knowledge, it represents the first dataset of this type. Other empirical analyses of sensitive topics such as extortion and corruption, in fact, typically measure the intensity of the activity of the extortion racket or the amounts of bribes through indirect questions in surveys (see, e.g. Frye and Zhuravskaya, 2000 and Svensson, 2003).[6]

The paper is organized as follows. In Section 2 we describe our dataset; in Section 3 we present the stylized facts emerging from the dataset; in Sections 4 and 5 we describe and solve the basic theoretical model of a monopolistic Mafia optimally choosing extortion as a function of some observable variable; in Section 6 we present the results of the econometric

[4]Choi and Thum (2004) also study extortion as imposed by public officers and not by criminal organizations.

[5]Interestingly, when Olken and Barron (2009, p. 446) estimate the elasticity of payments at check-points with respect to a measure of cargo value, they find a value of 0.072 which is consistent with the values of the elasticities of *pizzo* to firm's size that we estimate in this paper.

[6]See also Olken and Barron (2009, Fn. 1) for a similar remark.

analysis; in Section 7 we offer a discussion on the economics of extortion on the basis of our findings and conclude.

2 The Dataset

As mentioned in the Introduction, one of the main contributions of this paper is to analyze a newly built dataset combining information on the exact amounts of money paid to the mafia with data from firms' financial statements. Data on *pizzo* come from the *Fondazione Chinnici* of Palermo.[7] This database contains information on extortionary activities by the Sicilian mafia, *Cosa Nostra*, in the nine provinces of Sicily in the period 1987-2007. The main source of evidence is court documents, supplemented by interviews with magistrates.[8] For a recorded extortion case, the database contains information on: 1) the identity of the extorted firm; 2) its sector; 3) its administrative location (province, city, address); 4) its *Mandamento*;[9] 5) the amount of *pizzo*; 6) the period in which the payment took place;[10] 7) the type of payment: monthly, annual, one-off;[11] 8) the presence of additional impositions (e. g. forced supply, forced hiring of workers, etc.); 9) references on the source of data.[12] Overall, the database on extortion contains information on approximately 2300 episodes of extortion but the exact amount of *pizzo* is reported for a subset of cases only.

For this paper we extracted from the original database all episodes for which the exact amount extorted is recorded and that refer to monthly payments, for a total of 488 data points, representing the largest subset of observations with information on the amount paid.[13] With respect to this subset, we were able to match information on the extorted firm to data in

[7] These data were collected in 2007 for the project on "The Costs of Illegality" (*I costi dell'illegalità*), whose results are published in La Spina (2008). See also Asmundo and Lisciandra (2008) for details.

[8] Approximately, 200 documents were examined and 45 interviews were conducted.

[9] A *Mandamento* is an area subjected to the control of one or more Mafia families. According to Paoli (2003, p. 45) a mandamento is: "a district incorporating an average of three mafia families."

[10] For most cases, the dataset contains information on whether *pizzo* was paid *until* a certain year t. In few cases, the period corresponds to an interval, i.e. 1995-1998, in even fewer cases to individual years. Therefore, for all firms we are able to identify a year in which the *pizzo* was paid with certainty, i.e. the upper limit of the specified interval, or the individual year. This will be the year of *pizzo* payment that we will consider in our analysis.

[11] Payments to the Mafia are made on monthly basis, on two-three installments per year, typically on special occasions such as Christmas and Easter, or in a single solution. We label the payments of the second type "annual".

[12] In particular, excerpts from relevant court documents and the name of police operation/investigation from which the documentation originates.

[13] Other observations for which the amount of pizzo is recorded refer to annual and one-off payments (156 and 327 respectively). The analysis of the different types of payments will be the subject of further research.

the database of the Italian Chamber of Commerce (CCIAA) for 334 observations.[14] Of these, 145 (corresponding to 134 firms)[15] are limited liability companies (*Società di capitali*), and 189 (corresponding to 189 firms) are partnerships (*Società di persone*).[16] For both groups we collected other firms' data from CCIAA (i.e. legal form, initial year of activity, initial capital, number of employees, number of local units, information on whether the firm is still active at the date of collection of the data).[17] For limited liability firms only we collected the financial statements available in the period 1992-2011.[18] We did not find any financial statement for 14 out of the 134 matched limited liability firms.[19]

Our final sample is therefore made of two groups of observations. For partnerships, we have 189 data points referring to 189 firms with the amount of monthly *pizzo*, the year in which it was paid and other data from CCIAA except financial statements. For limited liability companies, we have 120 firms with the same data on *pizzo*, and financial statements. This subsample will be the main focus of our analysis. Finally, since we have financial statements for different years, we could have performed a panel data analysis by imputing the amount of pizzo paid to the year where the balance sheet was available. Unfortunately, we do not have sufficient information on time variation of *pizzo* in the data to perform such type of analysis. Therefore we chose to average the balance sheet data over the available years and perform a cross-section analysis.

The obvious shortcoming of this dataset is that the original sample of *pizzo* episodes is non-random. We defer to Appendix A for a description of the method we followed to assess the capacity of the dataset to represent the phenomenon of organized crime and the population of firms. Here we just note two reasons why the selection bias should be somewhat attenuated. First, an episode appears in the database for different reasons. An episode was recorded because the extorted firm reported the crime or because, during an investigation that might have been or not related to extortion, evidence was found of the case, or because a statement was provided by an investigated person about the extorted firms. Second, court documents were supplemented with interviews with magistrates. Third, there is no evidence that the collection of court documents and the extraction of data were biased towards, e.g.,

[14] In Italy, any legal economic activity must be officially registered at the local Chamber of Commerce. The impossibility of matching all data on *pizzo* depends on errors or incomplete data in the datasets that matched.

[15] Eleven observations refer to firms for which more cases of extortion were reported.

[16] Therefore, approximately 68% of observations (334/488) were matched to data from CCIAA.

[17] Data on financial statements were extracted from the CCIAA database in July 2012.

[18] Only this type of firms are required by the Italian law to file a copy of the balance sheet at the local Chamber of Commerce.

[19] We transformed all monetary values in the financial statements in constant 1995 prices.

one province, one economic sector, etc.

2.1 Descriptive Statistics

In this section we provide some descriptive statistics of our sample and show its distribution across provinces, years and sectors.

Figure 1 reports the estimated distributions of the amounts of *pizzo* for the two groups of matched firms in our dataset: limited liability (145 obs.) and partnerships (189 obs.).

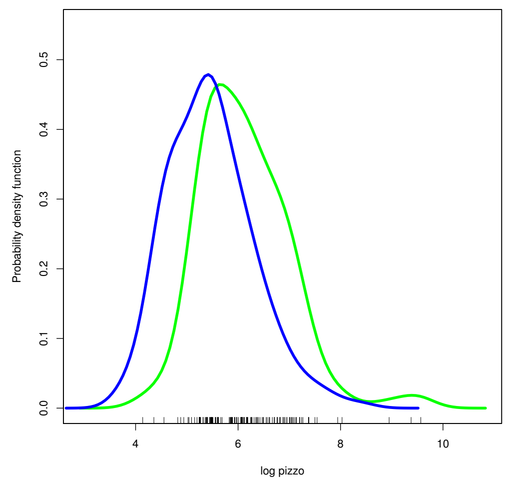


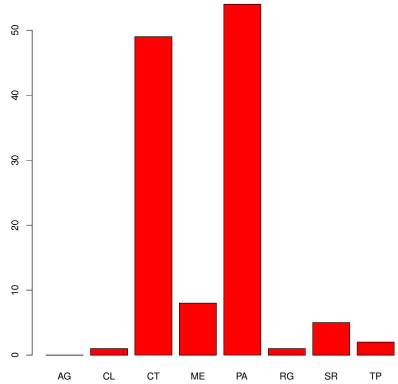
Figure 1: Distribution of (log) pizzo values: limited liability firms (green) and partnerships (blue). Mean and standard deviation of the two distributions are, respectively: 785 Euros (sd 1634) and 351 (sd 460).

Figure 1 shows that the two distributions are remarkably different: in particular the values of *pizzo* paid by limited liability companies are on average higher and more dispersed. As remarked, financial statements are available for limited liability firms only. This will be the source for the firms' quantitative data, in particular for the key variables for our analysis, the measures of size. In what follows, therefore, we focus on the observations on *pizzo* corresponding to 120 matched limited liability firms for which such data are available.

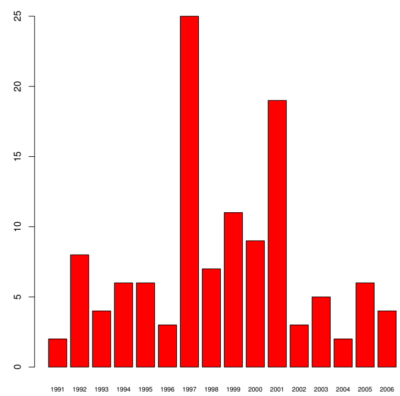
Figure 2 presents the distribution of these 120 observations per province, year and sector. From Figure 2(a) it can be observed that most of the observations come from the provinces of Palermo (PA) and Catania (CT), the largest Sicilian provinces. Provinces such as Caltanissetta (CS) and Ragusa (RG) have very few observations, while Agrigento (AG) and Enna (EN) have none.[20] Figure 2(b) shows that the observations are unevenly distributed

[20]The nine Sicilian administrative provinces are: Trapani (TP), Palermo (PA), Messina (ME), Agrigento

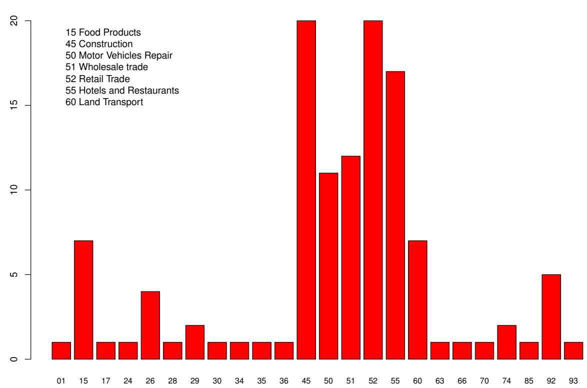
over the period 1991-2006,[21] while Figure 2(c) highlights that some sectors appear relatively often in the dataset.[22] The most represented sectors are: "Food Products", "Construction", "Motor Vehicles Repair", "Wholesale trade", "Retail trade", "Hotels and Restaurants" and "Land Transport".



(a) Distribution per province



(b) Distribution per year



(c) Distribution per sector

Figure 2: Distribution of observations per province, year and sector

How well does this sample capture the salient characteristics of the population of extorted firms? In Appendix A we present a detailed analysis of this issue and show that the

(AG), Caltanissetta (CL), Enna (EN), Catania (CT), Ragusa (RG), and Siracusa (SR). The provincial population shares, averaged over the period 1992-2006, are: Trapani (8.6%), Palermo (24.8%), Messina (13.2%), Agrigento (9.2%), Caltanissetta (5.5%) , Enna (3.6%), Catania (21.1%), Ragusa (5.9%), Siracusa (8%). Data on provincial population levels are from the Italian National Statistical Institute (ISTAT), see `http://demo.istat.it/`.

[21] The imputation of a specific year to a *pizzo* payment is explained in Footnote 10.

[22] Sectors are classified according to the 2-digit ATECO 2002 classification. See Table 8 in Appendix B.

relatively high sample shares in the provinces of CT and PA, and in low-tech sectors and the Construction sector is consistent with the available evidence that the Mafia is particularly strong in those provinces, and that those sectors are particularly vulnerable to Mafia penetration, following the early insights of Schelling (1971). We claim therefore, that the sample represents a good approximation of a random sample. To correct for possible over- and under-representation in our sample, however, in our econometric analysis we will also estimate WLS regressions.

3 *Pizzo* and Firms' Charachteristics: Stylized Facts

In this section we present a preliminary analysis aimed at establishing some stylized facts about the relation between the values of the *pizzo* imposed by the Mafia and some firm's characteristics: size and sector. Due to limitations in the data, in our cross-section analysis for every firm we will consider the relationship between the recorded *pizzo* value and: i) firms' sector, ii) a cross-section average values of measures of firms' size, where averages are calculated from the available data for each firm.[23]

The mean *pizzo* value and standard deviation in our sample of 120 observations amount to 689 and 1313 Euros. By deleting a strikingly high value of approximately 14000 Euros, we obtain a value of mean and standard deviation of 577 and 490 Euros. Remarkable differences, however, exist across sectors. Table 1 reports the sectoral *pizzo* averages for the most represented sectors.

[23]That is we abstract from whether these data refer to financial statements from years before or after the year of the payment. As noted in Footnote 10, most of the years that we associate to a payment of *pizzo*, refer to the final year of a period in which payments were made. Therefore, to establish a relation between the amounts paid and indicators of firms' characteristics from financial statements' data, one should only consider balance sheets for years not posterior to year of payment. The available balance sheets, however, lack a large amount of information for the periods preceding the years of payment. This is due to the fact that a relevant number of observations on *pizzo* refer to the early nineties, while a regular collection of data in electronic form by the CCIAA started at the end of that decade (personal communication from CCIAA staff in Palermo). The consequence is that when we restrict the analysis to data for the year preceding (or equal to) the year of the payments, we lose approximately 30% of observations. If we compute, however, the correlation of the financial statements' data averaged before and after the year of payment, for the relevant measures of size we utilize in the following, we find a value of approximately 0.8. Therefore, in our cross-section analysis we will consider averages computed over all available years, under the assumption that missing values for the averages on years before payment are are well proxied by the values computed by averaging after the year of payment.

Sector	Average *pizzo*	# obs.
45 Construction	1513 (860)	20 (19)
60 Land Transport	880	7
52 Retail Trade	681	20
50 Motor Vehic. Repair	451	11
55 Hotels and Restaurants	395	17
15 Food Products	304	7
51 Wholesale Trade	292	12

Table 1: Average *pizzo* in the most represented sectors. Numbers in parenthesis refer to the deletion of the highest observation in the Construction sector

The highest value is exhibited by the Construction sector, and the lowest by Wholesale Trade. The highest *pizzo* value belong to a firm in the Construction sector: deleting such value strongly reduces the sector average below the one computed for the Land Transport sector.[24] Most of these differences are statistically significant. For example, in the case the highest value is deleted, a simple Welch t-test returns a p-value of less than 1% for the difference between the average *pizzo* value of the Construction sector and the average values for Motor Vehicles Repair, Hotels and Restaurants, Food Products and Wholesale trade.[25]

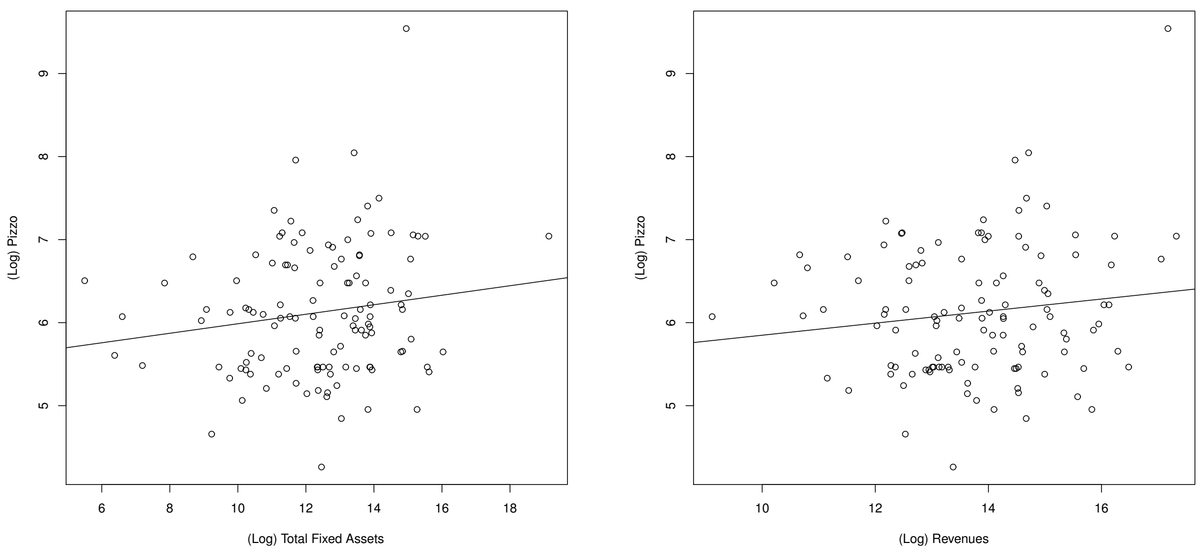
To analyze the relationship between *pizzo* and firm size, we will consider as our primary measure firms' total fixed assets, consistently with the model presented in Section 4.[26] As a secondary measure we will consider firms' revenues.[27] Figure 3 present bivariate scatterplots of the relation between *pizzo* and these two measures of size.

[24]Similar results are highlighted by Asmundo and Lisciandra (2008) who, however, do not analyze quantitative firm-level data as in this paper.

[25]Tests conducted using Land Transport for comparisons return less significant results due to the low number of observations in this sector.

[26]Firms' total fixed assets is the most comprehensive balance sheet measure of firms' capital, and include physical capital, financial assets and intangible assets, such as the book value of a brand. The correlation with physical capital in our sample is, however, almost 1.

[27]The correlation between total fixed assets and revenues for the firms in our sample is 0.58.



(a) *Pizzo* and Total Fixed Assets (b) *Pizzo* and Revenues

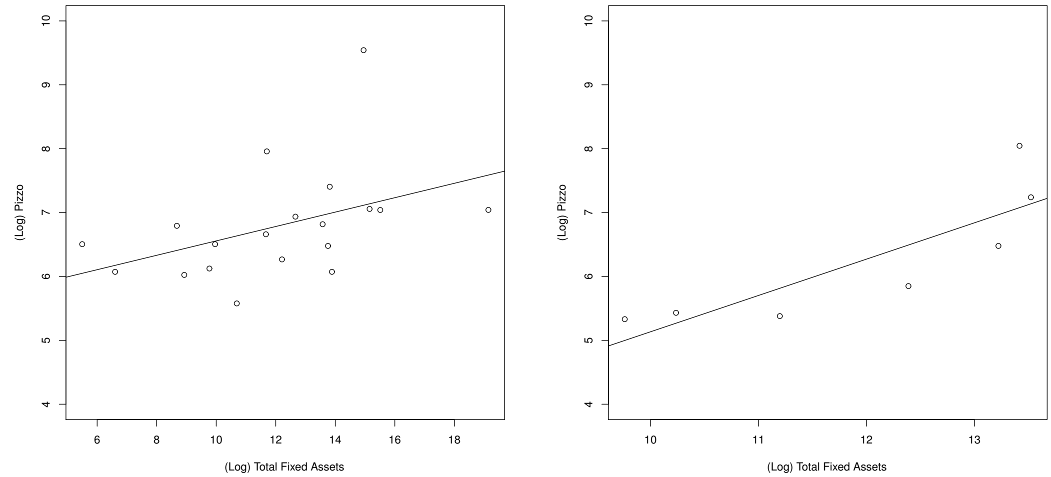
Figure 3: The relation between the amount of *pizzo* and measures of firms' size: total fixed assets and revenues.

It is apparent from Figure 3 that the relationship between *pizzo* and firm's size is rather flat: the estimated elasticities with respect to the two measures range between 0.06 and 0.07 and are barely significant.[28] Given the large differences in the average *pizzo* identified across sectors, we check if these point to differences across sectors in the relation between *pizzo* and size. Simple bivariate regressions suggest that differences indeed exist. Figures 4 and 5 contain the scatterplots of the relation between *pizzo* values and size (measured by Total Fixed Assets) for sectors exhibiting a positive relation and for sectors exhibiting a flat relation.

The only two sectors characterized by a positive and significant relationship are Construction and Land Transport: the estimated elasticities are, respectively, 0.11 (p-value: 0.07) and 0.57 (p-value: 0.02). For all the other sectors, the estimated elasticity is never significantly different from zero, implying that the Mafia sets a flat marginal "tax" rate.[29]

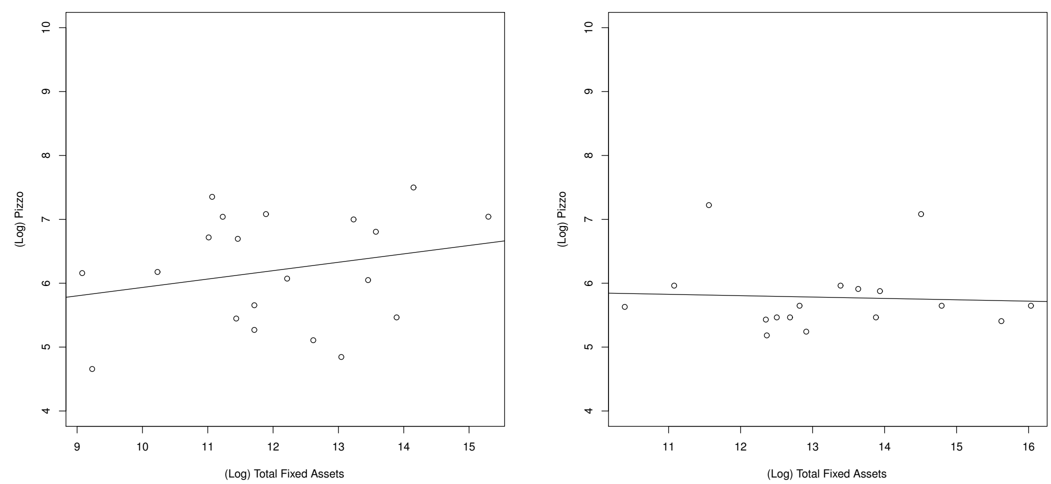
[28]Removing the highest *pizzo* has negligible consequences on the estimated bivariate relationship. Figure 16 in Appendix D.1 reports the scatterplots of the relation of *pizzo* with two alternative measures of size, related to the size of the workforce: the number of employees and the amount of personnel costs. The estimated bivariate relationships are very similar to the ones in Figure 3.

[29]Results are slightly affected by deleting the highest *pizzo* value (the coefficient for Construction decreases to 0.07 (p-value: 0.08). Furthermore, considering revenues as the proxy for size, also Motor Vehicles Repair exhibits a significantly positive elasticity (0.23 p-value: 0.02), while the elasticity for Construction becomes marginally non-significant (p-value: 0.11).



(a) Construction (b) Land Transport

Figure 4: *pizzo* and firms' size (Total Fixed Assets), sectors with positive relations



(a) Retail Trade (b) Hotels and Restaurants

Figure 5: *pizzo* and firms' size (Total Fixed Assets), sectors with flat relations

To sum up, we identified the following stylized facts on the relation between the level of *pizzo* set by the Mafia and firm's sector and size: 1) the amount of *pizzo* varies significantly across sectors; 2) the amount of *pizzo* varies little with the size of the firm. Stylized facts 1) and 2) can be reconciled by the stylized fact: 3) the elasticity between *pizzo* and size varies across sectors: it can be moderately positive or nil.

In Section 4 we present a theoretical model that can account for the observed stylized facts, while in Section 6 we present the econometric analysis of the identified relations.

4 The Model

In this section we describe the basic theoretical model of a monopolistic Mafia that chooses the amount to extort from each firm so as to maximize its profits. Firms are heterogeneous. There is a continuum of potential firms indexed by a productivity parameter θ, distributed according to $G(\theta)$ with strictly positive density $g(\theta)$ on the interval $[\theta_L, \theta_H] \subseteq \mathbb{R}_+$. We assume that the distribution G satisfies monotone hazard rate so that $H(\theta) = (1 - G(\theta))/g(\theta)$ is decreasing. If a firm opens for business, its profits gross of any amount forced to pay to Mafia are $\theta f(k) - rk$, where k is a choice variable for the firm meant to broadly represent firm's size. The function f is increasing, strictly concave and satisfies $f(0) = 0$ and $f' \to \infty$ as $k \to 0$. In our empirical analysis we will consider different measures of size, but here to fix ideas k can be understood to be capital which costs r per unit invested.

Gross profits of firm θ are the amount of money the Mafia can appropriate. A perfectly informed Mafia would be able to observe θ. It would then force each firm's type to choose the size level that maximizes profits, and fix the extorted amount exactly equal to profits so as to leave each firm with zero net profits. Instead, we assume that θ is private information of the firm. The Mafia knows only its distribution G, in addition to r and the function f. Last, the Mafia is able to observe k and thus it can tailor extortion to the size of the firm.

The timing we have in mind is the following. The Mafia is a Stackelberg leader and its existence is commonly known by firms. The Mafia does not know θ, and neither it can observe revenues nor profits. It can only observe k after a firm has chosen it. Its demand for extortion is summarized by the function $x(k)$, which gives the amount of money x asked from a firm which has chosen k, and the promise of a punishment z to be inflicted to a non-compliant firm. We assume that Mafia has enough reputation concerns that it finds always optimal not to renegotiate the extortion in case of compliance and to inflict the punishment to a non-compliant firm. Firms know both $x(k)$ and z when choosing whether to open for business. Once in the market, they choose the amount of observable k optimally and whether to pay the extortion amount x or suffer the punishment cost z. Formally, the sequence of moves is as follows:

1. Nature extracts type θ that is observed only by the firm.
2. Mafia proposes an extortion function $x(k)$, given the level of firepower z.
3. The firm decides whether to open for business having observed both $x(k)$ and z. If the firm does not open for business it gets the outside option, normalized to zero.
4. If the firm is in business, it chooses k to maximize profits, given $x(k)$ and z.
5. The firm decides whether to be compliant, in which case it pays $x(k)$, or to refuse to pay, in which case it suffers the cost z.

In the following sections our objective will be to characterize theoretically the optimal choice of the extortion function $x(k)$ and to compare it to the empirical counterpart in our dataset.[30]

5 Optimal Extortion Function

We note that the game induced by our timing is one of incomplete information where the uninformed party moves first and commits to a function $x(k)$ of the optimal choice of the follower. The assumption on commitment allows the problem to be mapped into a principal-agent framework in which the Mafia is the principal and the firm is the agent. To solve for the optimal extortion function we can appeal to the revelation principle to find the optimal direct mechanism $\{k(\theta), x(\theta)\}$, where $k(\theta)$ is the choice of size and $x(\theta)$ is the payment from type θ. As profits are linear in the amount extorted, we will actually solve for the pair $\{k(\theta), \pi(\theta)\}$, where π corresponds to equilibrium *net profits* of the firm: $\pi(\theta) = \theta f(k(\theta)) - rk(\theta) - x(\theta)$. We will then recover the indirect mechanism $x_*(k)$ which implements the optimal choice. This will be our theoretical *pizzo function.*

We begin the analysis from the compliance choice of the firm in stage 5. It is clear that the firm will choose to be compliant with extortion if $x(\theta) \leq z$, which will be satisfied

[30]In Appendix A we explain why, in line with Schelling (1971), firms with less visible output and profits, such as high-tech firms, are less likely to appear in the sample. In terms of the model, we argue that for such firms the Mafia is not only unable to perfectly observe their profits, but neither it observes signals that are correlated with profits, such as k or the distribution of θ.

for every θ by z large enough. In stage 4, anticipating compliance in equilibrium, the firm chooses optimally k, which in this context amounts to incentive compatibility. Since the model satisfies single crossing it is standard to verify that incentive compatibility is satisfied if and only if $\pi'(\theta) = f(k(\theta))$ and $k'(\theta) \geq 0$. Again anticipating future decisions, in stage 3 firm will decide to enter the market if $\pi(\theta) \geq 0$, since the outside option is independent of firm's type. These points allow the optimization problem of stage 2 of the Mafia to be written in the following compact form:

$$\begin{aligned} &\max_{k(\theta),\pi(\theta)} \int_{\theta_l}^{\theta_h} (\theta f(k(\theta)) - rk(\theta) - \pi(\theta))dG \qquad \text{(mp)} \\ &s.t. \quad \pi'(\theta) = f(k(\theta)) \\ &\pi(\theta) \geq 0,\ \theta f(k(\theta)) - rk(\theta) - \pi(\theta) \leq z,\ k'(\theta) \geq 0. \end{aligned}$$

The solution is found applying standard techniques in contract theory and assumes that the Mafia is strong enough that the firm always prefers to pay exortion instead of suffering the punishment.[31]

Proposition 1 *Suppose $z > x_{mp}(\theta_h)$. The solution $(k_{mp}(\theta), \pi_{mp}(\theta))$ to (mp) and the associated payment function $x_{mp}(\theta)$ satisfy (i) and (ii):*

(i) $(\theta - \frac{1-G(\theta)}{g(\theta))})f'(k_{mp}(\theta) = r$;

(ii) $\pi_{mp}(\theta) = \int_{\theta_l}^{\theta} f(k_{mp}(s))\,ds$. Therefore the payment function is

$$x_{mp}(\theta) = \theta f(k_{mp}(\theta)) - rk_{mp}(\theta) - \int_{\theta_l}^{\theta} f(k_{mp}(s))\,ds.$$

(iii) Denoting with $\theta_{mp}(k)$ the inverse of $k_{mp}(\theta)$ the optimal solution can be implemented via an extortion function $x_*(k) = x_{mp}(\theta_{mp}(k))$.

(iv) $x_*(k)$ is concave.

In our model, firms are heterogeneous in terms of the productivity parameter θ, which measures how firms transform investment in size into revenues. A perfectly informed Mafia would force each type to choose the efficient size, i.e. the one that maximizes profits: $\theta f'(k) = r$. In addition, it would choose extortion exactly equal to gross profits, so that $\pi(\theta) = 0$

[31]The proof is in Appendix C.

for all types. Thus a perfectly informed Mafia is able to appropriate all profits without generating inefficiencies.

As θ is not observable but size is, the Mafia uses the observation of k as a proxy for productivity. This results in the pizzo function $x_\star(k)$. This behavior is consistent, for example, with anecdotal accounts of Mafia tailoring *pizzo* to the number of shop windows facing the street that a store has (Scaglione, 2008, p. 150), provides anecdotal evidence of this aspect. Through the pizzo function the Mafia tries to expropriate profits but, crucially, it also affects the investment choices of firms. This dual role generates a trade-off, from the Mafia's perspective, between efficiency and expropriation.

If Mafia fully expropriated efficient profits, more productive firms would invest less than the optimal size, thus decreasing Mafias' revenue. One possibility for the Mafia is then to simply decrease the level of pizzo for more productive, hence larger, firms. However, this is very costly as they are also the ones with larger profits to be expropriated. Another possibility is to discourage underinvestment by inducing a larger distortion for smaller firms. And indeed in Proposition 1, point (i) shows that in equilibrium Mafia maximizes profits by having more productive firms choose larger size k (H is decreasing), but size is distorted downward compared to the efficient level for all types except the highest ($G(\theta_h) = 1$). Thus asymmetric information generates an inefficiency through lower than optimal firm size for almost all firms. Crucially for our empirical exercise, point (iv) shows that the Mafia induces the desired level of investment by using a concave extortion function. Thus the Mafia is able to discourage excessive underinvestment of more productive firms by imposing a larger *marginal* pizzo on smaller investment levels, and marginal pizzo ends up being decreasing in size. Finally, point (ii) shows that asymmetric information limits the Mafia's ability of profit expropriation. In equilibrium, all firms except the one with the lowest productivity are left with positive net profits ($\pi(\theta_l) = 0$ and $\pi(\theta) > 0$). Since in equilibrium size is increasing in productivity, this also implies that the Mafia expropriates a larger share of profits from smaller firms.

Our model thus yields two simple testable implications, which we take to the data in the next section. The first is that the *pizzo* function should be concave. In Subsection 6.1, we take the functional form

$$pizzo = B \cdot k^{\alpha} \text{ with } B > 0 \tag{1}$$

to our dataset and test whether $0 < \alpha < 1$.[32] The second is that the incidence of pizzo

[32] In Appendix C we show that this functional form is consistent with a parametric specification of the distribution function and the production function.

on profits should be larger for smaller firms. In Subsection 6.2 we measure the incidence of *pizzo* with the fraction of operating profits appropriated by the Mafia, the *pizzo rate*, and we test whether it is decreasing in firm's size.

6 Econometric Analysis

In this Section we carry out an econometric analysis of the relationship between the amount of *pizzo* paid by a firm and a measure of its size. Specifically, we will focus on the value of firms' total fixed assets, as a proxy of k, as they appear in firms' financial statement data.

6.1 Estimating the *Pizzo* Function

In this section we provide an econometric analysis of the relation between *pizzo* paid by the firms in our sample and firms' size, taking into account how this relationship changes across sectors. Our aim is to search for support to the stylized facts identified in Section 3. The theoretical model suggests that extortion should be nonlinear. Since the firms in our sample differ in sector, province and years in which they paid *pizzo*, we allow the coefficients B and α from Eq. (1) to vary according to these characteristics. In our first regression, we let B vary across characteristics and restrict α to be the same across sectors. The empirical counterpart of Eq. (1) after taking logarithms is:

$$log(pizzo_i) = \gamma + \alpha \cdot log(k_i) + SECT_i + YEAR_i + PROV_i + \epsilon_i \tag{2}$$

where $pizzo_i$ is the amount of *pizzo* paid by firm i, $SECT_i$ is a dummy for the firm's sector, $YEAR_i$ is a dummy for the year in which firm i paid, to control for possible time effects, $PROV_i$ is a dummy for the province of firm i to control for possible, unobservable, differences in the policy of different Mafia families operating in different geographical areas.[33]

We estimate Eq. (1) with OLS as well as with WLS. As noted in Appendix A.2, our sample can feature over- and under-representation of firms in some provinces or sectors. For this reason, we run WLS estimations based on a simple weighting scheme, in which the weight for the observation of a firm in sector i in province j, is given by $1/share_{i,j}$, where $share_{ij}$ is the average provincial share of firms in sector i in province j over the period

[33] As remarked in Section 2.1, the original dataset included information on the *Mandamento* (see Footnote 9) where the extorted firm is located. However, paucity of data prevents from the consideration of this piece of information. The identification of different Mafia "taxation" policies by *Mandamento* remains an interesting topic for future research.

1995-2006.[34] Table 2 reports the results.

Table 2: Pizzo and Firm's Total Fixed Assets (OLS and WLS)

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	4.884***	4.011***	4.657***	5.051***	3.403***	4.553***
	(1.015)	(1.128)	(1.242)	(1.262)	(0.787)	(1.181)
Total Fixed Assets	0.054	0.091**	0.080**	0.046	0.138***	0.112***
	(0.034)	(0.035)	(0.035)	(0.038)	(0.034)	(0.036)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	119	119	119	119	119	119
Adjusted R^2	0.253	0.195	0.338	0.423	0.567	0.653
Residual Std. Error	0.681	0.707	0.641	3.599	3.118	2.791
F Statistic	2.814***	1.951***	2.341***	4.937***	6.153***	5.939***
Note:				*p<0.1; **p<0.05; ***p<0.01		

The estimated elasticities in Table 2 take on significant values comprised between 0.09 and 0.14. The relevance of the Sector dummy is apparent: when it is excluded (see Models 1 and 4), the coefficient on the elasticity of *pizzo* with respect to firm's size is not significant. The Time dummy also seems to exert a non-negligible effect, in particular by increasing the estimated values of the elasticities.[35]

As a further sensitivity test, we run the regressions of Tables 2 excluding the observation on the highest *pizzo*, treated as an outlier.[36] Table 9 in Appendix D show that results are not remarkably affected: the absolute value of the estimated elasticity is somewhat lower, lying in the interval $(0.06 - 0.13)$, but it is still significant with the exception of Models 1 and 4.[37]

In Section 3 we showed that, in bivariate regressions, there exist differences across sectors in the slope of the relationship between *pizzo* and size. To test this hypothesis, we modify Eq. (2) introducing an interaction term between $log(k_i)$ and a dummy for sectors with a

[34] The population of firms considered is the active joint-stock companies in Sicily. The source of data is the *Movimprese* database (`https://www.infocamere.it/movimprese`). Results are not affected by the use of an alternative weighting scheme in which the weight for an observation is given by $1/share_{i,j}$, where $share_{ij}$ is the average share of firms in sector i in province j over the total number of Sicilian firms for the period 1995-2006. Results are available upon request.

[35] Excluding the Province dummy does not alter the results.

[36] The value of this *pizzo* is correctly reported from court documents. We have not, however, a decisive argument to consider this value as a simple anomaly or evidence that the level of *pizzo* can also be set by the Mafia, in some instances, at a very high level.

[37] In Appendix D.2.1 we report the results of estimations in which we consider firm's revenues as an alternative measure of size. The magnitudes and significance of the estimated coefficients are largely consistent with those obtained with firm's total assets.

positive slope in Figure 4, that is Construction and Land Transport. Therefore the equation to be estimated becomes

$$log(pizzo_i) = \gamma + \alpha \cdot log(k_i) + \beta \cdot D \cdot log(k_i) + SECT_i + YEAR_i + PROV_i + \epsilon_i \quad (3)$$

where $D = 1$ if firm i belongs to Construction or Transport. Table 3 contains the results.

Table 3: Pizzo and Firm's Total Fixed Assets (OLS and WLS), with dummy on the slope

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.493***	4.429***	5.221***	5.187***	3.903***	5.344***
	(0.980)	(1.191)	(1.353)	(1.253)	(0.802)	(1.224)
Total Fixed Assets	0.040	0.057	0.045	0.050	0.100***	0.075*
	(0.032)	(0.047)	(0.048)	(0.038)	(0.038)	(0.040)
Total Fixed Assets x D	0.048***	0.073	0.072	0.028	0.191**	0.175*
	(0.014)	(0.068)	(0.069)	(0.017)	(0.086)	(0.088)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	119	119	119	119	119	119
Adjusted R^2	0.326	0.196	0.339	0.433	0.586	0.667
Residual Std. Error	0.647	0.706	0.641	3.567	3.050	2.736
F Statistic	3.485***	1.930***	2.317***	4.926***	6.386***	6.131***
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 3 shows that, especially with WLS estimations, there appears a difference across sectors in the elasticities of *pizzo* with respect to total fixed assets. The elasticity for sectors different from Construction and Land Transport is estimated in a range between zero and 0.1, while the elasticity for these two sectors can be as high as 0.3. Results in Table 12 in Appendix D show that the cross-sector difference is even larger with revenues as a measure of size. In particular, all the OLS estimations return a significant coefficient for the interaction term. The magnitude of the estimated coefficients are slightly higher than those estimated for total fixed assets.

These pieces of evidence are consistent with the hypothesis that the Mafia applies different types of tariffs in different sectors. The higher elasticity in Construction and Land Transport suggests that the Mafia is better able to discriminate on the basis of size in these sectors.

We offer two possible explanations of this finding. One relies on the high knowledge that organized crime has of firms in some sectors, for example the Construction sector, allowing for control of operations and thus a better discrimination of firms' ability to pay.[38] The

[38] "Mafia organizations entirely control the building sector in Palermo - the quarries where aggregates

other rests on differences in technology. The relationship between size and ability to pay varies across sectors depending on the production function. The higher elasticity in the Construction and Land Transport may then depend on the fact that in these sectors profits are more sensitive in percentage terms to size than in other sectors.[39]

6.2 On the Incidence of Extortion on Profits

So far we identified the slope of the relationship between the amounts of *pizzo* and the size of the firm. Our findings show that the relationship is concave in levels, with the marginal *pizzo* paid for an euro invested in the size of the firm decreasing as size increases. A further question, which is still unsettled in the literature, is what is the actual fraction of gross profits paid as extortion, and how this incidence is correlated with size. In other words, we want to measure the degree of progressivity of Mafia "taxation".

To this purpose, we compute the average *pizzo rate*, given by the ratio of *pizzo* to the operating profits of the firms,[40] and evaluate it as a function of the size of the firm. Figures 6-9 present graphical evidence of the relationship between incidence and measures of size: total fixed assets and revenues.

In the left panel of each figure, we divide firms in quartiles of Total Fixed Assets and Revenues, and for each class we compute the mean and the median of the *pizzo rate*. In the right panel we report the log-log scatterplot of *pizzo rate* against the measure of size. From Figures 6-9 we note that the incidence of *pizzo* strongly decreases with the size of the firm, starting from very high values for the smallest firms.[41] Table 4 presents the results of OLS and WLS regressions of the *pizzo rate* on firm's total fixed assets, with the same set of control dummies we used in the previous section. The results confirm that the relationship

are mined, site clearance firms, cement plants, metal depots for the construction industry, wholesalers for sanitary fixtures, and so on" (Falcone and Turone 1982, quoted in Paoli, 2003, p. 167). For a recent account of Mafia penetration in the Transport sector in Sicily, see Palidda (2011).

[39]See also the discussion in Appendix C, where we show that under a parametric specification of our model a perfectly informed Mafia would force firms to choose the desired level of capital and then apply a linear tax to extract all the surplus. For our empirical specification, this would correspond to $\alpha = 1$ in Equation (1). Also, for that specification, in the presence of asymmetric information the elasticity of the optimal pizzo function with respect to size coincides with the elasticity of the production function with respect to size.

[40]This value refers to the difference between the revenues of the firm and the production costs. It abstracts, therefore, from other costs, such as interests, and from taxes. As such, it provides the "purest" measure of the profits from the typical activity of the firm. We compute the rate for firms in our sample having positive average operating profits in the period of observation.

[41]In the left panel bar graphs we exclude a single observation of a firm in the Land Transport sector having a large value of *pizzo* incidence, around 8 while the second highest observation is around 3, and which is in the third size quartile. This value is due to the fact that the firm has operating profits close to zero. This exclusion affects only the computation of the means, and it has no effect on the results of the regressions.

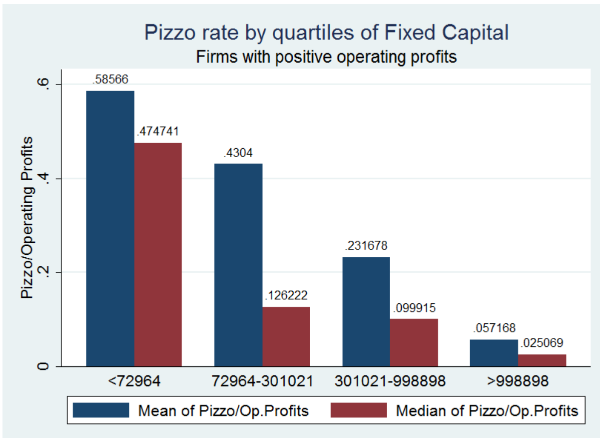


Figure 6: Pizzo rate and Total Fixed Assets: mean and median values per quartile

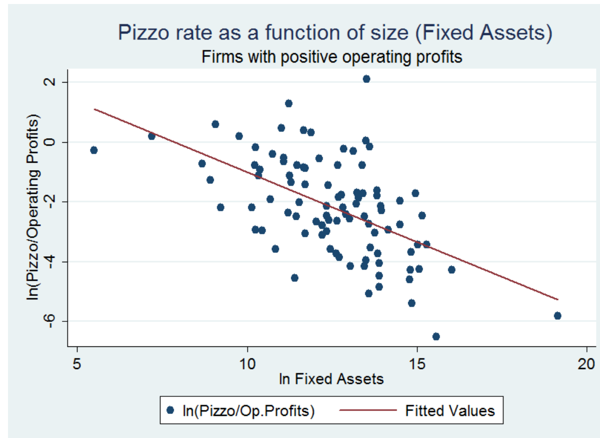


Figure 7: Pizzo rate and Total Fixed Assets

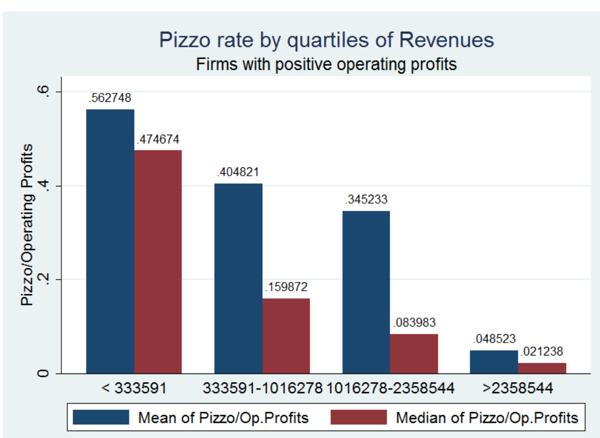


Figure 8: Pizzo rate and revenues: mean and median values per quartile

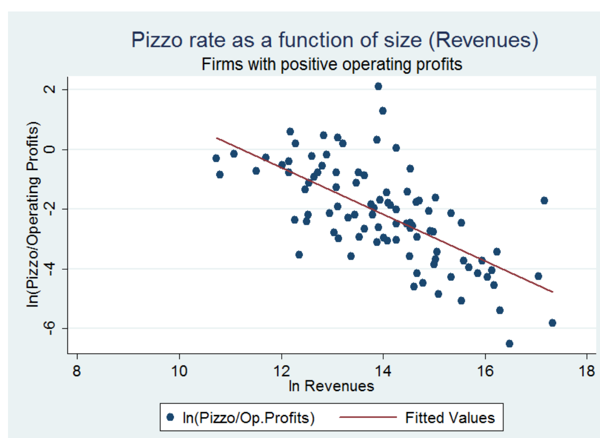


Figure 9: Pizzo rate and revenues

is significantly negative it is not driven by province, sector or time differences.[42]

Table 4: Pizzo Rate and Firm's Total Fixed Assets (OLS and WLS)

	Dependent variable:					
	log (pizzo rate)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−1.237	−0.268	−0.780	−2.820	−0.291	−0.622
	(2.112)	(2.144)	(2.660)	(2.863)	(1.733)	(2.281)
Total Fixed Assets	−0.498***	−0.475***	−0.529***	−0.516***	−0.490***	−0.614***
	(0.085)	(0.081)	(0.099)	(0.102)	(0.102)	(0.100)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	94	94	94	94	94	94
Adjusted R^2	0.349	0.405	0.410	0.616	0.804	0.875
Residual Std. Error	1.334	1.275	1.270	7.735	5.519	4.418
F Statistic	3.269***	3.111***	2.438***	7.772***	13.744***	15.416***
Note:						*p<0.1; **p<0.05; ***p<0.01

This exercise allows us to asses quantitatively the relevance of extortion for firms' profitability. There is substantial heterogeneity across class sizes and the incidence of pizzo decreases as size increases. The difference between the values of the *pizzo rate* for the smallest and largest firms in our sample appears striking: the smallest firms in our sample are taxed for a median value of more than 40%, while the largest are subject to an extortion rate around 2%, as largest firms are "taxed" for only approximately 2% of their operating profits. Overall, we find clear evidence that *Mafia taxation is regressive.*

6.3 A Comparison with State Taxation

In the previous section we highlighted that the structure of Mafia "taxation" is strongly regressive: it displays a modest or zero value of elasticity with respect to our chosen measures of size, and has an incidence on profits which strongly decreases with firms' size. In this section we compare the "taxation" imposed by organized crime to the official institution in charge of taxing firms and citizens: the State.

Table 5 contain the results from OLS and WLS regressions of log(taxes) on Total Fixed Assets.

The results in the Table show that the structure of State taxation is remarkably different from that of organized crime. The estimated value of the intercept is not statistically different

[42] Table 13 in Appendix D contains the results of the same regressions using revenues instead of total fixed assets, confirming the results of Table 4.

Table 5: Taxes and Firm's Total Fixed Assets (OLS and WLS)

	Dependent variable:					
	log (tax)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.855	1.081	1.404	−0.018	0.550	2.098
	(2.053)	(2.244)	(2.821)	(2.661)	(1.852)	(2.807)
Total Fixed Assets	0.578***	0.575***	0.594***	0.624***	0.632***	0.593***
	(0.071)	(0.075)	(0.085)	(0.088)	(0.099)	(0.104)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	111	111	111	111	111	111
Adjusted R^2	0.431	0.403	0.370	0.541	0.639	0.681
Residual Std. Error	1.353	1.386	1.424	7.378	6.544	6.155
F Statistic	4.784***	3.471***	2.434***	6.904***	7.498***	6.217***

Note: *p<0.1; **p<0.05; ***p<0.01

from zero, implying a value of the parameter B in Eq. (1) of approximately one. The estimated elasticity is instead much higher, taking on values between 0.58 and approximately 0.63. Since we are estimating constant elasticity functions, we can take as a measure of how regressive is the system the distance between the estimated elasticity and 1, the latter being elasticity when taxation is approximately linear (see, e.g., Kakwani, 1977, p. 71). We can see that elasticity is approximately 0.6 if measured by Total Fixed Assets.[43] These values are closer to 1 than our estimates of the elasticity of *pizzo*, so we can conclude that Mafia taxation is much more regressive than State taxation. We also compute a measure of State taxation incidence using the total taxes paid by the firm for the year, which is then averaged across years in the sample. For consistence with the measure we computed for *pizzo*, the incidence of State taxes is the ratio of total taxes and operating profits, and we name this variable the *tax rate*. We compare the two rates, as a function of our measures of size, in Figures 10 - 13.

In the left panel we report the median values per quartile of size for the two rates (again, for firms with positive operating profits) and in the right panel we compare the scatterplots and their linear fit.

[43]Table 14 in Appendix D.2.1 shows that the estimated elasticity with respect to revenues is approximately 1, corresponding to the case of linear taxation, which corresponds to the Italian taxation scheme for firms.

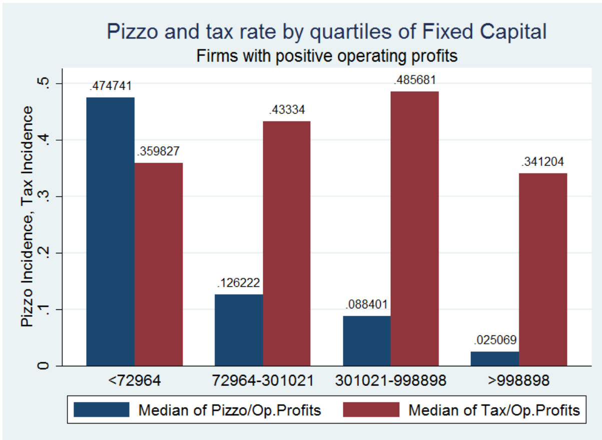


Figure 10: Pizzo and Tax rate by Total Fixed Assets: median values per quartile

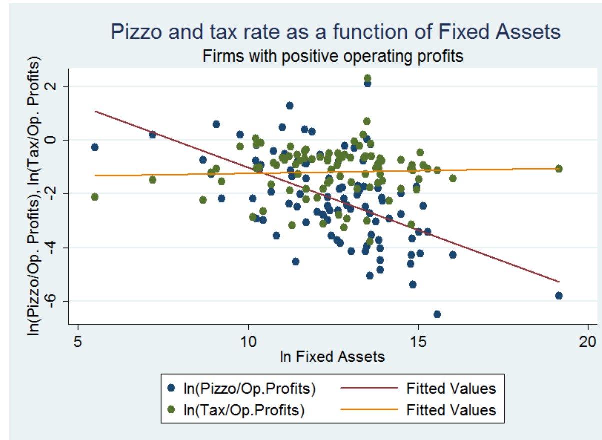


Figure 11: Pizzo and Tax rate by Total Fixed Assets

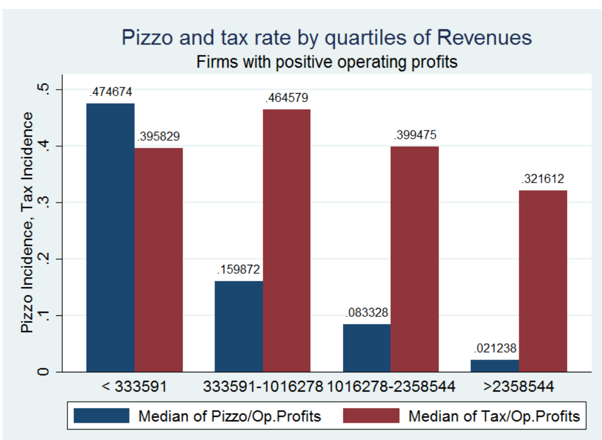


Figure 12: Pizzo and Tax rate by revenues: mean and median values per quartile

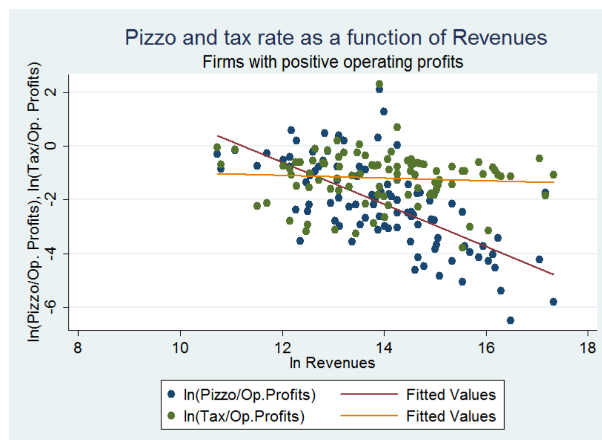


Figure 13: Pizzo and Tax rate by revenues

It is clear that the two rates behave differently as a function of size. While the *pizzo* rate is strongly decreasing, the tax rate stays constant or slightly increases as size increases, averaging to approximately 40% of operating profits. We note that firms in the smallest quartile of our sample are particularly vexated by the combined effect of State taxes and *pizzo*. If one takes operating profits as a measure of the value added produced by a firm, which can then be appropriated by the State or the Mafia through taxes or extortion, then we see that the percentage expropriated by the two institutions together sums approximately to 70% of value added for small firms

7 The Economics of Extortion: Concluding Remarks

In this paper we presented a theoretical and empirical analysis of extortion of firms operating in legitimate sectors by one criminal organization, albeit one of the most powerful, the Sicilian Mafia. Our main findings can be summarized as follows. (i) The relationship between pizzo and firm size is concave: marginal pizzo is decreasing. We find that the elasticity of the pizzo function is approximately 0.1, which implies in absolute terms that a firm expecting to enter the market at a small scale faces a large marginal pizzo. (ii) The fraction of profits appropriated by the Mafia decreases with size, so Mafia taxation is regressive.

These findings suggest some specific microeconomic channels through which extortion affects the economy. Extortion money is a cost that firms expect to pay when operating in a territory mostly dominated by the Mafia. Our results show that this added cost roughly behaves as an almost fixed cost. It increases rapidly at small scales, while it becomes somewhat flat at larger scales.[44] For firms operating at small scales it induces a large distortion in investment. Moreover for these firms it represents a form of barrier to entry in the market, thus limiting competition. Through this channel we can expect the emergence of oligopolistic markets, characterized by a small number of firms setting high prices and selling products of low quality.

Our results have also implications for the dynamics of development. An important source of growth for firms, being it in size or in productivity, is reinvestment of own profits. We have shown that the Mafia distorts investment, and thus profits, below first best and that it appropriates a large fraction of realized profits from small firms (up to 40% for the first size quartile), which in our model are also the less productive ones. The two effects compound in diminishing the amount of resources available to be further reinvested, thus hampering the potential for firms' growth. Another important source of firms' growth is access to external funds, namely bank loans. Also this channel is affected by the presence of organized crime. For the Italian case, there is evidence that in the presence of crime, and in particular of organized crime imposing extortion, interest rates on banks loans are higher, the effect being driven mainly by the increase in the interest rate spread on smaller firms. Moreover, firms are required to put up more collateral and they are credit rationed.[45] Our findings shed light on the possible mechanism at play. Conditioning on individual characteristics, in areas dominated by organized crime smaller firms are expropriated more, so they end up being

[44]Depending on the structure of the other costs, the average cost function including extortionary payments might become decreasing, thus making the market a potential natural monopoly.

[45]See the empirical estimates in Bonaccorsi di Patti (2009).

less profitable and limited in the chances of building up enough collateral to access further credit. Thus they end up being credit rationed and paying larger interests on bank loans.

These considerations point at the possibility that an economy where organized crime systematically imposes extortion on legitimate business may fall in a low-growth poverty trap.[46] As noted above, extortion as an almost fixed cost potentially generates non-convexities which induce the minimum efficient scale to be larger. Many poor individuals find themselves unable to invest their way out of poverty because of insufficient initial capital to enter above minimum scale, being also limited in the possibility of building up collateral to access credit and also due to the high cost of bank loans for the ones who can barely meet minimum scale. In turn, incentives for the poor to save are lower because the return to capital is low for low levels of investment. The mechanism at work is therefore similar to the one studied by Banerjee and Newman (1993) among others. The novel insight is that organized crime is responsible for *both* the non-convexities and the credit market imperfections. Deriving these implications in a full growth model for an economy plagued by extortion under asymmetric information and evaluating its empirical content, is an interesting topic for future research.

[46] The persistence of Sicily at low development levels is a well-documented fact. See, e.g., Lavezzi (2008) and the references therein.

Appendix

A On the Sample

Ideally, for an analysis like the one we propose in this paper, we should consider a random sample extracted from the population of extorted firms in Sicily. This population, however, is not observable. Since our sample is not random, a natural question is whether it is severely biased or it can nonetheless represent a good approximation of a random sample. In this Appendix we describe the procedure we followed to assess the representativity of our sample of the population of interest.

In particular, in Section A.1 we show that the restriction of the sample from the whole set of data on *pizzo* to the sample of matched data is not biased, while in Section A.2 we evaluate the representativity of our sample by exploiting two characteristics of the firms in the sample, their province and sector, and the fact that, although the population of extorted firms is not observable, the provincial and sectoral distributions of Sicilian firms are observable.

A.1 From the Original Sample to Our Sample

In Figure 14 we compare the distribution of the 488 (unmatched) observations on monthly *pizzo* to the distribution of 334 observations of the matched firms.[47] Figure 14 shows that the distribution of the smaller set of 334 observations doest not display remarkable differences, so that the deletion of the observations of the unmatched firms does not seem to bias the sample.

[47] Amounts of *pizzo* are expressed in logs to have a clearer visualization. Densities are estimated non-parametrically, using a normal kernel function with a normal optimal smoothing parameter. See Bowman and Azzalini (1997, p. 31).

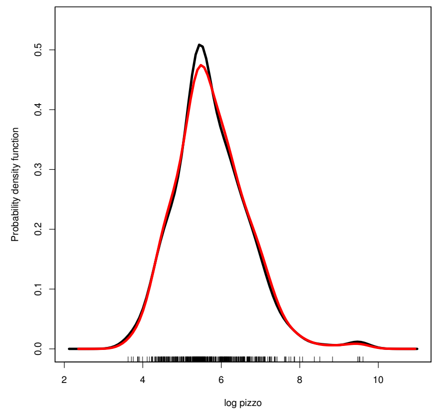


Figure 14: Distribution of (log) pizzo values: all observations on monthly *pizzo* (black) vs values for matched firms (red)

A.2 On the Provincial and Sectoral Distribution of Sample Data

In Section 2.1 we showed the provincial distribution of firms in our sample. In a random sample, it should approximate the provincial distribution of extorted firms in Sicily. As noted, such distribution is not observable. It is possible nonetheless to examine the provincial distribution of all firms in Sicily to draw some conclusions on possible biases in our sample along this dimension.

It can be easily shown that if the fraction of firms that pay the *pizzo* is the same in every province, than the provincial distribution of extorted firms coincides with the provincial distribution of all Sicilian firms. If, however, the fraction of firms in province i that pay *pizzo* is higher than the average provincial share of extorted firms, then the provincial share of extorted firms in province i is higher than the provincial share of all firms in province i. In a random sample approximating the population shares, therefore, the share of extorted firms in province i should be higher than the share of Sicilian firms in province i.

Table 6 compares the provincial distribution of observations in our sample with the provincial distribution of all firms.[48]

[48]The population is represented by the average number of joint-stock companies in Sicily active in the period 1995-2006. (the choice of the time interval is dictated by data availability). Data are from the *Movimprese* database (`https://www.infocamere.it/movimprese`), part of the CCIAA information system. The average total number of firms in the the period of interest is 20652, so that the size of our sample is 0.58% of the population.

	Sample (extorted firms)	Sicily (all firms)
TP	0.02	0.08
PA	0.45	0.24
ME	0.07	0.11
AG	0.00	0.06
CL	0.01	0.05
EN	0.00	0.02
CT	0.41	0.29
RG	0.01	0.06
SR	0.04	0.09

Table 6: Provincial distribution of firms: in the sample and in Sicily

In the provincial distribution of observations in our sample the share of firms from the provinces of Palermo (PA) and Catania (CT) is higher than the share of Sicilian firms in those provinces, and lower in the other provinces. This is consistent with the case in which Mafia is particularly strong in the provinces of PA and CT so that in these provinces a higher fractions of firms is extorted than the overall share of Sicilian firms, while in the other provinces the share of extorted firms is lower than the regional share. Is this actually the case? Confesercenti (2008, p. 12), a survey carried by a major Italian business association, reports that in the cities of Catania and Palermo, i.e. the provinces' capitals, the share of extorted firms is the highest in Sicily reaching 80%, while in provinces such as EN, SR and RG it is the lowest.[49] The over-representation of the provinces of Palermo and Catania in the sample is therefore consistent with this piece of evidence.

As a further check, we compare the distribution of sample observations to the distribution of measures of Mafia penetration at provincial level, under the hypothesis that where the Mafia is more pervasive, more firms are extorted. Calderoni (2011) discusses the measures of Mafia penetration existing in the literature, and proposes new measures. In general, these indicators are constructed by considering data on mafia-related crimes (including extortion), other indicators of the presence of the mafia (e. g. confiscated properties), or other socio-economic indicators.[50] Since this type of measurement necessarily involves some degree of

[49]No exact measures of such differences are, however, offered. The share of firms actually paying *pizzo* is a so-called *dark number*, i.e. a number difficult to observe in particular for the high under-reporting of many crimes. See Asmundo and Lisciandra (2008) for further discussion for the case of extortion in Sicily.

[50]See Calderoni (2011) for a thorough discussion.

arbitrariness, we report different indicators taken from Calderoni (2011). Table 7 contains the values of different indicators of Mafia presence in the nine Sicilian provinces.[51]

	IPM	POPM	ICC	Mirate	Mirank
PA	35.50	90.90	45.90	50.37	83.22
CL	33.10	95.20	44.20	42.20	84.50
CT	52.40	79.70	33.70	32.12	82.50
TP	29.40	91.00	31.60	29.42	77.86
AG	28.90	95.90	23.20	23.52	71.75
EN	29.20	73.80	30.40	17.21	57.74
SR	38.60	88.70	16.60	12.74	50.71
RG	28.40	57.50	25.60	17.83	61.82
ME	31.90	57.10	21.10	15.44	60.82

Table 7: Indicators of Mafia presence at provincial level

For ease of comparison, the order of the provinces in Table 7 is based on the average ranking of provinces in the indices presented.[52] This order suggests that the "quantity" of Mafia in the provinces of Palermo (PA), Caltanissetta (CL) and Catania (CT) is relatively high, while it is relatively low in the provinces of Siracusa (SR), Ragusa (RG) and Messina (ME). According to this comparison, we might have under-representation in our sample of the extorted firms of the province of Caltanissetta (CL).

Now we highlight the characteristics of the sectoral distribution of the observations in our sample. In Figure 2(c) we reported the sectoral distribution of the sample observations, showing that some sectors appears more frequently than others. Following the argument we proposed for the provincial distributions, in Figure 15 we compare the sectoral distribution of the sample with the sectoral distribution of the Sicilian firms.[53]

[51] The reported indices are: *IPM* (*Indice di penetrazione mafiosa*): constructed by *Eurispes* (*Istituto di Studi Politici Economici e Sociali*) in 2010. It is based on Mafia-related crimes (extortion, mafia association, drug smuggling, etc.) and socio-economic indicators (unemployment, trust in institutions, etc.), and aims at measuring the capacity of the Mafia to penetrate a territory (see Calderoni, 2011, fn. 11). *POPM*: constructed by *Censis* (*Centro Studi Investimenti Sociali*) for the years 2004-2006. It measures the population of each province living in municipalities with recorded Mafia activities, as a percentage of total provincial population. ICC (*Indice di contesto criminale*), was proposed by Calderoni and Caneppele (2009) in a study of infiltration by organized crime in public procurement, and is based on an average of various mafia-related murders, including indicators of infiltration in public procurement, for a period approximately covering the decade 1995-2005. *Mirank* and *Mirate* are new indices proposed by Calderoni (2011) based on four dimensions of Mafia activities: mafia-type associations, mafia murders, city councils dissolved for mafia infiltration, assets confiscated to organized crime. *Mirate* is based on averages of the four indicators, while *Mirank* is based on the average *ranking* of each province along the four dimensions. The period covered goes from the early eighties to the interval 2007-2009. For further details and references see Calderoni (2011).

[52] In particular, PA and CL have the same average ranking, as well as SR and RG.

[53] The population of Sicilian firms is the same utilized in Table 6.

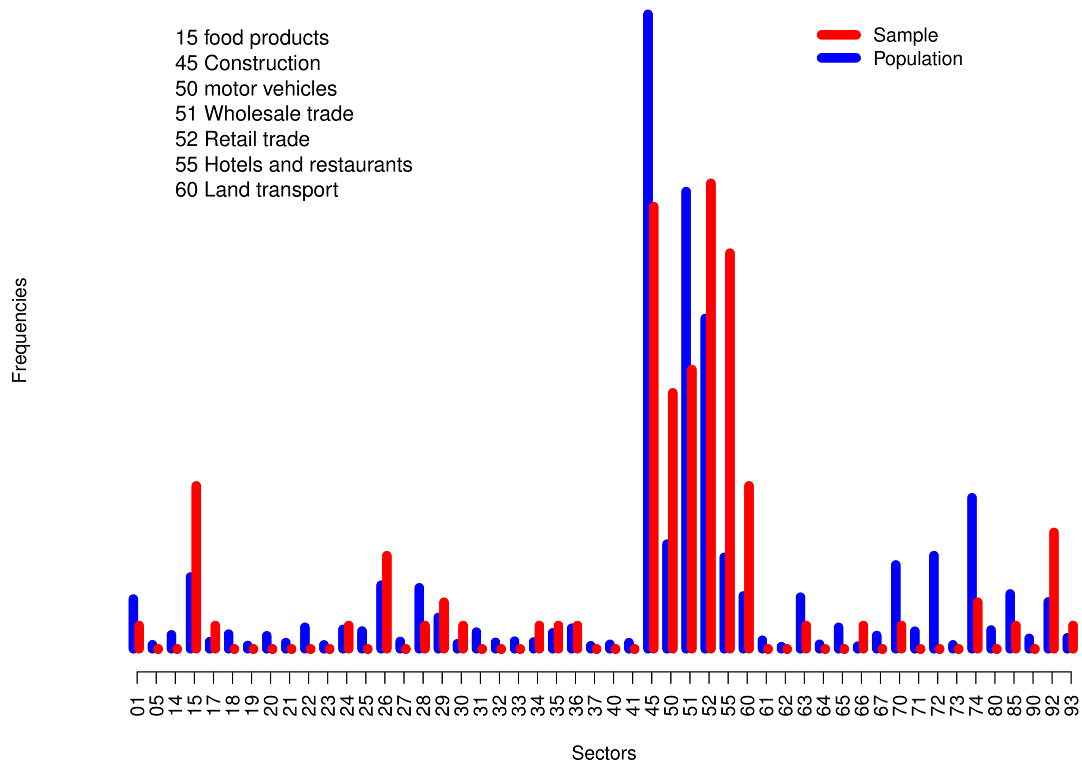


Figure 15: Distribution of observations across sectors: our sample and population.

Figure 2(c) shows that the most represented sectors in the sample are: "15 Food Products", "45 Construction", "50 Motor Vehicles Repair", "51 Wholesale trade", "52 Retail trade", "55 Hotels and Restaurants" and "60 Land Transport", while Figure 15 shows that most of these sectors are over-represented in our sample with respect to the population shares, in particular: "Food Products", "Motor Vehicles Repair", "Retail Trade", "Hotels and Restaurants", and "Land Transport".

Along the same line of reasoning proposed for the provincial distribution, it is easy to show that, if some sectors are more vulnerable to extortion, i.e. the fraction of firms in sector j that pay *pizzo* is higher than the average sectoral share of extorted firms, then the sectoral share of extorted firms in sector j is higher than the sectoral share of all firms in sector j. In a random sample approximating the population shares, therefore, the share of extorted firms in sector j should be higher than the share of Sicilian firms in sector j.

Indeed, Schelling (1971) argued that some characteristics of a firm make it more vulnerable to penetration of organized crime through extortion. In particular, Schelling (1971) argued that it is easier for racketeers to extort firms with more visible output or profits, since firms' owners in this case cannot hide their capacity to pay the *pizzo*. In addition, Gambetta and Reuter (1995, p. 122) posit that a high territorial characterization of the economic activity, as in the case of: "construction, transport, and street-hawkers", increases the probability of being extorted by organized crime, because a major aim of these organizations is controlling the territory.

Assuming that a proxy for the visibility of output and profits is the technological level of the firm, i.e. that low-tech firms produce "simple" goods and services whose value or quantity can be easily observed by a *mafioso*, we show that most of the sectors over-represented in the sample are characterized by a low technological level.[54] According to the EUROSTAT classification,[55] in fact, the "Food Products" sector is a "low-tech" sector, while the sectors of "Motor Vehicles Repair", "Retail Trade", "Hotels and Restaurants" are "less-knowledge intensive" (LIS) service sectors.[56] The "Wholesale Trade" sector, who has a relatively high share in the sample, although it is not over-represented, is also classified as LIS. The tight link with the territory of the firms in the "Construction" and "Land Transport" sectors contributes to explain the relatively high number of firms in such sectors in the sample: in particular "Land Transport" is also over-represented, while "Construction" is not.[57] The under-representation of "Construction" in the sample can be explained by the fact that the type of "pizzo" that is typically imposed to the firms in this sector takes the form of one-off payments, which is made once the construction site is opened.[58] For the under-representation of "Wholesale Trade", we conjecture that such economic activities are less observable than, for example, retail trade activities. Among the sectors that clearly appear under-represented in the sample, the sectors of 70, 72 and 74, respectively "Real estate activities", "Computer and related activities" and "Other business activities" stand out: two of them (72 and 74) are classified as "knowledge-intensive sectors".

Overall, on the basis of the analysis carried out so far, we claim that our sample represents a fairly good approximation of a random sample of the extorted firms of Sicily. Such a sample, with respect to the provincial and sectoral distribution of Sicilian firms, should contain a relatively high share of firms from the Provinces of Palermo and Catania and from the sectors

[54]Table 8 contains all details on the sectoral distributions.

[55]See: `http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`.

[56]An exception is Sector 92 ("Recreational, cultural and sport activities") which is over-represented in the sample but is classified as "knowledge intensive".

[57]According to the EUROSTAT classification, "Land Transport" is also a LIS sector, while "Construction" is not classified.

[58]In the dataset of *Fondazione Chinnici* on such payments, almost half of the observations belong to the Construction sector.

that the theory suggest are more vulnerable to extortion, or more tightly connected to the territory. In any case, in our econometric analysis we will also perform a WLS estimation of the relationship between *pizzo* and the firms' characteristics that takes into account possible under- and over-representation of firms in our sample with respect to purely random sample.

B Sectoral Distributions

Table 8 reports the description of the sectors appearing in our sample, the sectoral shares in the sample and in the population, and the technological level of each sector. Sectors are classified according to the ATECO 2002 classification,[59] while the sectors' technological level is based on the EUROSTAT definition.[60]

[59]Available (in Italian) at: `http://www3.istat.it/strumenti/definizioni/ateco/ateco2002.pdf`
[60]See: `http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`.

ATECO	Sector Name	% (sample)	% (pop.)	Tech. Level
01	Agriculture, hunting and related service activities	0.8	1.8	NC
05	Fishing	-	0.1	NC
14	Other mining and quarrying	-	0.5	NC
15	Manufacturing: food products and beverages	5.9	2.6	L
17	Manufacturing: textiles	0.8	0.3	L
18	Manufacturing: clothing products	-	0.5	L
19	Manufacturing: leather and leather products	-	0.1	L
20	Manufacturing: wood and wood products	-	0.5	L
21	Manufacturing: wood pulp	-	0.2	L
22	Manufacturing: paper and paper products; publishing and printing	-	0.8	L
23	Manufacturing: coke, refined petroleum products and nuclear fuel	-	0.1	ML
24	Manufacturing: chemicals, chemical products	0.8	0.7	MH
25	Manufacturing: rubber and plastic products	-	0.6	ML
26	Manufacturing: other non-metallic mineral products	3.4	2.3	ML
27	Manufacturing: metallurgy	-	0.3	ML
28	Manufacturing: fabricated metal products	0.8	2.2	ML
29	Manufacturing: machinery	1.7	1.1	MH
30	Manufacturing: office equipment	0.8	0.2	H
31	Manufacturing: electrical machinery	-	0.6	H
32	Manufacturing: communication equipment	-	0.2	H
33	Manufacturing: medical and optical equipment	-	0.3	H
34	Manufacturing: motor vehicles	0.8	0.2	MH
35	Manufacturing: other transport equipment	0.8	0.6	MH
36	Manufacturing: furniture; other manufacturing	0.8	0.7	L
37	Recycling	-	0.1	L
40	Electricity, gas, steam and hot water supply	-	0.2	NC
41	Collection, purification and distribution of water	-	0.2	NC
45	Construction	16	22.9	NC
50	Motor vehicles	9.2	3.8	LK
51	Wholesale trade	10.1	16.5	LK
52	Retail trade	16.8	11.9	LK
55	Hotels and restaurants	14.3	3.3	LK
60	Land transport	5.9	1.9	LK
61	Water transport	-	0.3	K
62	Air transport	-	0.1	K
63	Transport activities; travel agencies	0.8	1.9	LK
64	Post and telecommunications	-	0.2	K
65	Financial intermediation	-	0.8	K
66	Insurance and pension funding	0.8	0.1	K
67	Activities auxiliary to financial intermediation	-	0.5	K
70	Real estate activities	0.8	3	LK
71	Renting of machinery and equipment	-	0.6	LK
72	Computer and related activities	-	3.4	K
73	Research and development	-	0.1	K
74	Other business activities	1.7	5.5	K
80	Education	-	0.7	K
85	Health and social work	0.8	2	K
90	Sewage and refuse disposal, sanitation	-	0.4	LK
92	Recreational, cultural and sport activities	4.2	1.7	K
93	Other services	0.8	0.4	LK

Table 8: Description of sectors represented in the sample and in the population of firms. Technological level: H: Hi-technology; MH: medium-high technology; ML: medium-low technology; L: low technology; K: knowledge-intensive; LK: less knowledge-intensive; NC: not classified.

C Proofs for Section 4

Proof of Proposition 1.

(i) Integrating the envelope condition we have $\pi(\theta) = \pi(\theta_l) + \int_{\theta_l}^{\theta} f(k(s))ds$. Substituting in the objective function and integrating by parts the choice of $(k(\theta), \pi(\theta_l))$ reduces to

$$\max_{k(\theta),\pi(\theta_l)} \int_{\theta_l}^{\theta_h} \left(\left(\theta - \frac{1-G(\theta)}{g(\theta)} \right) f(k(\theta)) - rk(\theta) \right) d\theta - \pi(\theta_l).$$

Thus $\pi(\theta_l) = 0$ and pointwise maximization yields the formula in the Proposition. The monotone likelihood condition ensures that $k_{mp}(\theta)$ is increasing.

(ii) By the previous point, the rent function $\pi_{mp}(\theta) = \int_{\theta_l}^{\theta} f(k_m p(s))ds$ solves the maximization problem, thus the transfer function can be computed from $\pi = \theta f(k) - rk - x$.

(iii) Since $k_{mp}(\theta)$ is strictly increasing, the inverse $\theta_{mp}(k)$ exists and it is strictly increasing. Define $x_*(k) = x_{mp}(\theta_{mp}(k))$, so that

$$x_*'(k) = \frac{d}{dk} \left(\theta_{mp}(k) f(k) - rk - \int_{\theta_l}^{\theta^{mp}(k)} f(k^{mp}(s))ds \right) = \theta_{mp}'(k) f(k) - rk.$$

Type θ maximizes $\theta f(k) - rk - x_*(k))$, whose first derivative is zero when $\theta = \theta_{mp}$.

(iv) The previous point showed that the pizzo function $x_*(k)$ implements $(k_{mp}(\theta), x_{mp}(\theta))$ and thus $x_*'(k) = \theta_{mp}(k) f'(k) - r$. By the first order condition of the mafia we have $\theta_{mp}(k) f'(k) - r = H(\theta_{mp}(k)) f'(k)$. Hence $x_*''(k) < 0$ since $f'' < 0$, $H' < 0$ and $\theta_{mp}'(k) > 0$. ■

Our empirical specification is based on taking to the data a function of the form $x(k) = Bk^{\alpha}$. A parametric specification of the model that yields exactly this form is the following. Assume that θ is distributed on $[0, \infty]$ according to an exponential distribution with parameter $1/B$, thus $g(\theta) = B^{-1} e^{-B^{-1}\theta}$ and $H(\theta) = B$. Assume also $f(k) = k^{\alpha}$ with $0 < \alpha < 1$. In such a case, types $[0, B]$ are excluded (they choose $k = 0$), while types $[B, \infty]$ choose $k_{mp}(\theta) = (\alpha/r)^{1/(1-\alpha)}(\theta - B)^{1/(1-\alpha)}$. For types not excluded we then have

$\theta_{mp}(k) = rk^{1-\alpha}/\alpha + B$. Therefore Proposition 1 yields the following pizzo function

$$\begin{aligned}
x_*(k) &= \theta_{mp}(k)f(k) - rk - \int_B^{\theta_{mp}(k)} f(k_{mp}(s))ds \\
&= (rk^{1-\alpha}/\alpha + B)k^\alpha - rk - (\alpha/r)^{\alpha/(1-\alpha)} \int_B^{rk^{1-\alpha}/\alpha+B} (s-B)^{\alpha/(1-\alpha)}ds \\
&= Bk^\alpha + rk/\alpha - rk - (1-\alpha)(\alpha/r)^{\alpha/(1-\alpha)}(r/\alpha)^{1/(1-\alpha)}k \\
&= Bk^\alpha.
\end{aligned}$$

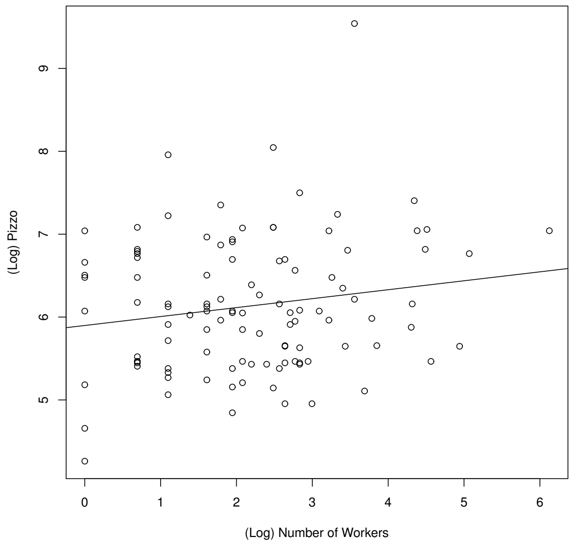
We also note here that under the alternative assumption of perfect information the mafia would impose the efficient level of capital to each firm type, that is $k_{fb}(\theta) = (\theta/r)^{(1-\alpha)}$ and fully appropriate all profits. In terms of the relation between pizzo and observable capital we would have the *linear* relationship $x_{fb}(k) = rk(1-\alpha)/\alpha$. Thus in the context of this parametric specification, non linearity (and specifically, strict concavity) of the relationship between pizzo and capital also constitutes evidence against the assumption of perfect information.

D Additional Results

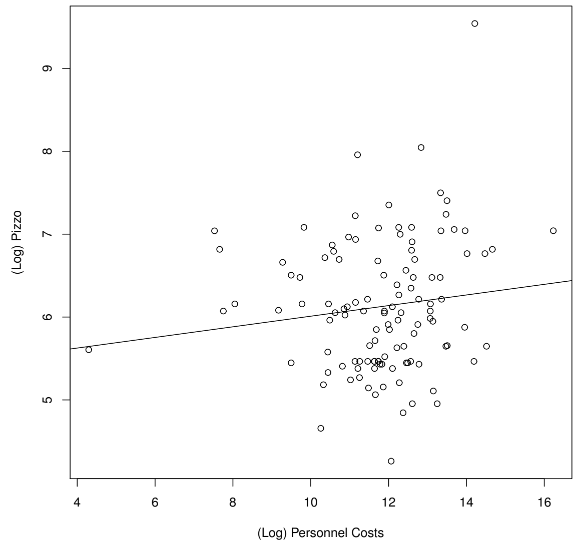
In this Appendix we report additional results.

D.1 Scatterplots

Figure 16 presents the scatterplots of the bivariate relationships between *pizzo* and two measures of size, related to the workforce: number of employees and personnel costs. While the personnel cost is regularly reported in the financial statements, the number of employees is not, but may appear in the documents accompanying the financial statements. For every firm, we extracted all the available information on this number and averaged across the period we are studying, although in the vast majority of cases we have only one data per firm.



(a) *Pizzo* and Number of Employees



(b) *Pizzo* and Personnel Costs

Figure 16: The relation between the amount of *pizzo* and other measures of firms' size

D.2 Regressions

D.2.1 Other Regressions with Total Fixed Assets and Revenues

Table 9 contains the results of the models estimated in Table 2 excluding the highest level of *pizzo*.

Table 9: Pizzo and Firm's Total Fixed Assets (OLS and WLS), excluding highest pizzo

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.728***	4.315***	5.360***	5.262***	3.473***	4.748***
	(0.946)	(1.044)	(1.144)	(1.257)	(0.780)	(1.174)
Total Fixed Assets	0.035	0.068**	0.059*	0.042	0.133***	0.105***
	(0.031)	(0.033)	(0.032)	(0.038)	(0.034)	(0.036)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	118	118	118	118	118	118
Adjusted R^2	0.263	0.190	0.352	0.427	0.572	0.657
Residual Std. Error	0.622	0.653	0.583	3.567	3.083	2.760
F Statistic	2.899***	1.913**	2.413***	4.955***	6.205***	5.972***
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 10 contains the estimation of the models of Table 2 which consider firm revenues as a measure of firm's size, while Table 11 contains the estimation of the same models excluding the highest *pizzo* value.

Table 10: Pizzo and Firm's Revenues (OLS and WLS)

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.143***	2.899**	4.391***	5.954***	2.328**	4.241***
	(1.173)	(1.323)	(1.442)	(1.376)	(1.147)	(1.461)
Total Fixed Assets	0.035	0.145***	0.091*	−0.013	0.179***	0.129**
	(0.048)	(0.053)	(0.053)	(0.047)	(0.059)	(0.062)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	No	No	Yes	No
Observations	117	117	117	117	117	117
Adjusted R^2	0.232	0.213	0.313	0.408	0.559	0.638
Residual Std. Error	0.695	0.703	0.657	3.658	3.158	2.860
F Statistic	2.590***	2.045***	2.175***	4.639***	5.901***	5.549***
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: Pizzo and Firm's Revenues (OLS and WLS), excluding highest pizzo

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	6.284***	3.766***	5.493***	6.236***	2.567**	4.592***
	(1.096)	(1.251)	(1.344)	(1.371)	(1.146)	(1.464)
Total Fixed Assets	−0.001	0.090*	0.047	−0.020	0.164***	0.113*
	(0.044)	(0.051)	(0.050)	(0.046)	(0.059)	(0.062)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	116	116	116	116	116	116
Adjusted R^2	0.248	0.195	0.326	0.414	0.562	0.641
Residual Std. Error	0.632	0.654	0.599	3.620	3.129	2.832
F Statistic	2.723***	1.929***	2.233***	4.686***	5.915***	5.564***
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 12 shows the results of estimation of Eq. (3) when revenues is the measure of firm's size

Table 12: Pizzo and Firm's Revenues (OLS and WLS), with dummy on the slope

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.549***	4.485***	6.201***	6.028***	4.089***	6.040***
	(1.118)	(1.529)	(1.658)	(1.370)	(1.288)	(1.600)
Revenues	0.035	0.043	−0.015	−0.008	0.070	0.031
	(0.046)	(0.073)	(0.073)	(0.046)	(0.070)	(0.072)
Revenues x D	0.045***	0.207*	0.215**	0.022	0.331***	0.313**
	(0.013)	(0.104)	(0.104)	(0.016)	(0.123)	(0.130)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	117	117	117	117	117	117
Adjusted R^2	0.310	0.239	0.344	0.414	0.589	0.661
Residual Std. Error	0.658	0.692	0.642	3.639	3.050	2.768
F Statistic	3.267***	2.172***	2.320***	4.568***	6.354***	5.921***
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13 contains the results of regressions of the *pizzo rate* on firm's revenues.

Table 13: Pizzo Rate and Firm's Revenues (OLS and WLS)

	Dependent variable:					
	log (pizzo rate)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	4.260**	5.235**	4.798*	4.325*	5.138**	4.327
	(2.086)	(2.488)	(2.651)	(2.208)	(2.314)	(2.638)
Revenues	−0.809***	−0.720***	−0.808***	−0.888***	−0.720***	−0.814***
	(0.095)	(0.109)	(0.112)	(0.082)	(0.126)	(0.122)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	94	94	94	94	94	94
Adjusted R^2	0.524	0.460	0.552	0.804	0.823	0.884
Residual Std. Error	1.141	1.215	1.107	5.518	5.243	4.245
F Statistic	5.650***	3.639***	3.542***	18.386***	15.454***	16.786***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14 contains the results of estimations of the elasticities of firms' taxes with respect to firms' revenues.

Table 14: Taxes and Firm's Revenues (OLS and WLS)

	Dependent variable:					
	log (tax)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−4.679**	−6.049**	−5.449*	−5.935***	−8.245***	−5.962**
	(1.984)	(2.364)	(2.818)	(2.086)	(2.111)	(2.935)
Revenues	0.904***	0.908***	0.952***	0.928***	1.046***	0.988***
	(0.082)	(0.095)	(0.106)	(0.073)	(0.111)	(0.124)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	No	Yes	Yes
Observations	111	111	111	111	111	111
Adjusted R^2	0.580	0.517	0.509	0.748	0.743	0.758
Residual Std. Error	1.162	1.246	1.256	5.467	5.521	5.362
F Statistic	7.911***	4.925***	3.536***	15.865***	11.612***	8.648***

Note: *p<0.1; **p<0.05; ***p<0.01

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