ARTICLE IN PRESS

Journal of Comparative Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Comparative Economics

journal homepage: www.elsevier.com/locate/jce

The economics of extortion: Theory and the case of the Sicilian Mafia☆

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A R T I C L E I N F O

JEL classification:
K42
O17
R11
D86

Keywords:
Organized crime
Mafia
Extortion racketeering
Economic development
Optimal taxation

A B S T R A C T

This paper studies extortion of firms operating in legal sectors by a profit-maximizing criminal organization. We develop a simple taxation model under asymmetric information to find the Mafia optimal extortion as a function of firms' observable characteristics, namely size and sector. We test the predictions of the model on a unique dataset on extortion in Sicily, the Italian region where the Sicilian Mafia, one of the most ancient criminal organizations, operates. In line with our theoretical model, our empirical findings show that extortion is strongly concave with respect to firm size and highly regressive. The percentage of profits appropriated by the Mafia ranges from 40% for small firms to 2% for large enterprises. We derive some implications of these findings for market structure and economic development.

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 experience the presence of powerful *Mafias* that 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, in recent years criminal organizations have caused a cumulative loss in GDP of 16%.

The presence of a strong criminal organization in the region is a symptom of institutional weakness. In fact, Mafia-type organizations represent instances of "extra-legal governance" (Gambetta, 1993, Varese, 2014) providing a specific service, protection, which would otherwise be provided by the State. Although the literature on institutional quality and economic development mostly points

☆ Previous versions of this paper circulated with the titles: "Extortion, Firm's Size and the Sectoral Allocation of Capital", and "The Economics of Extortion: Theory and Evidence on the Sicilian Mafia". The initial stages of this project were carried out when M. Lavezzi was visiting Nuffield College as *Jemolo Fellow* and the Department of Economics at UCI. We thank both institutions for their exceptional hospitality. We thank four anonymous referees and one editor for their comments and criticisms. We are grateful to the *Fondazione Chinnici* for providing us with the database on extortion and the Chamber of Commerce of Palermo for granting us access to data on companies' financial statements. For comments and suggestions, we thank Diego Gambetta, Giovanni Mastrobuoni, Ferdinando Monte, Nicola Persico, Michele Polo, Wojtek Przepiorka, Andy Postlewaite, Shanker Satyanath, Stergios Skaperdas, Federico Varese, conference participants in Toulouse (EEA-ESEM), Petralia (Applied Economics Workshop), Warsaw (EALE), Trento (SIE), Livorno (*Structural Change and Growth*), and seminar participants in Irvine, Palermo, Rome Tor Vergata (CEIS seminars), and Nicosia. We thank G. Mellia, R. Musotto, S. Presti, G. Romano, and G. Tortorici for excellent research assistance. Financial support from Italian MIUR (PRIN: "Structural Change and Growth") is gratefully acknowledged. Usual disclaimer applies.

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https://doi.org/10.1016/j.jce.2023.05.003
Received 15 February 2022; Received in revised form 19 May 2023; Accepted 21 May 2023

out cross-country differences (see e.g. Acemoglu et al., 2005 for a comprehensive account of this literature), Italy displays significant cross-regional variation in institutional quality, as highlighted since the work of Putnam et al. (1994). Southern regions, i.e. the ones in which strong criminal organizations appeared and are still widespread, are those characterized by the lowest institutional quality (see the recent work of Acemoglu et al., 2017, for a discussion of the origins of the Sicilian Mafia and of its long-term economic consequences). Indeed, in the case of Russia, Frye and Zhuravskaya (2000) find that institutional weakness coupled with heavy regulation increases the probability that a shop owner has contacts with private protection organizations.[1]

Being a provider of extra-legal governance, Mafias implement their own taxation system. In particular they impose extortion, i.e. the forced extraction of resources, on 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*[2] paid by a sample of Sicilian firms, matched with data from their financial statements. Our aim is to understand how Mafia establishes the amount of money that businesses are forced to pay on the basis of their characteristics, namely size, and how this relationship varies by sector. In particular, we identify the stylized facts of the relationship between *pizzo* and firm size and sector and then show that they can be accounted for by a taxation 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 firm size and the amount of *pizzo* paid.

Our main findings are the following. The log of *pizzo* moderately increases with the log of firm size: the estimated elasticity of *pizzo* with respect to size is approximately 0.1, which implies a strongly concave relationship between *pizzo* and firm size, characterized by the marginal and average *pizzo* decreasing with size. The elasticities vary by business sector: in some sectors such as construction and transportation 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 business 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 enterprises.

These findings suggest specific microeconomic channels through which organized crime negatively affects economic growth: (i) by erecting barriers to entry, (ii) by stifling small businesses which, in an environment where access to credit can be difficult because of crime itself,[3] have limited resources to expand, and thus (iii) creating the conditions for a poverty trap based on non-convexity in the cost function.[4]

Our work is strongly influenced by the seminal contribution of Schelling (1971) on the economics of organized crime. Specifically, Schelling identifies the characteristics that make a company 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 contrast, in large companies, a *mafioso* would have to wander numerous floors of offices before eventually finding somebody to threat. Furthermore, he points out that companies with more observable profits or revenues can be easier targets of the racket because it would be difficult for such firms to claim an incapacity to meet the extortionary requests. Based 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 an extorted business, the choice of the amount the Mafia demands given size and sector.

Our work complements the existing literature on the economic analysis of extortion in different respects. A notable contribution is Konrad and Skaperdas (1998), who propose a model of extortion in which costly investment in destructive capacity and asymmetric information on firm value cause the emergence of conflict between the criminal organization and the extorted business, leading to an 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 extorted on observable characteristics correlated with private information (namely size), thus incentive compatibility induces distortion in productive choices and possibly exclusion from the market.

Aleksander (1997) studies the extortion racket in 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 local market conditions, she finds that Mafia "taxation" was regressive, as the highest burden from extortion was imposed on companies 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 the use of actual data on extortion with theirs. However, the kind of extortion analyzed by Olken and Barron (2009) refers to officers and should be more correctly classified as corruption.[5] In the case studied by Olken and Barron (2009) criminal organizations can provide protection to truck drivers along

[1] Other 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 sulfur mines (Buonanno et al., 2015) or of citrus fruits (Dimico et al., 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, Mastrobuoni and Patacchini (2012) on the internal structure of criminal organizations, Slutzky and Zeume (2020) on the effect that organized crime exerts on different dimensions of businesses' activities: the level of competition, innovativeness, and competition for public funds.

[2] *Pizzo* is the Sicilian word for the money extorted by the Mafia.

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

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

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

the route against the payment of a quasi-fixed fee. Differently, in our study the focus is on extortion imposed on legal businesses by organized crime, which can price-discriminate among firms based on observable characteristics, such as size.

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 size that we estimate in this paper. Furthermore, in a study of extortion by the Russian Mafia, Varese (2001, p. 107) finds that the kiosk owners he interviewed reported paying to the local racket a quasi-fixed amount of protection money, irrespective of what their turnover actually was. The explanation advanced by Varese (2001, p. 107) is that collecting precise information on each individual kiosk would have cost too much to the criminal organization, which consequently found it more convenient to set a quasi-fixed price. Interestingly, Varese (2001, p. 108) finds that in some instances the local Mafia could send an accountant to try to estimate the turnover of a business, to at least partially overcome the asymmetric information problem. These contributions, overall, suggest that the validity of our theoretical framework and empirical findings might extend beyond the case of the Sicilian Mafia.[6]

Being focused on Mafia extortion of legal businesses, our work is also complementary to the theoretical analyses of the case in which the State and the Mafia compete to tax companies, as in the seminal model of Grossman (1995) and in the more recent work of Alexeev et al. (2004). In these articles firms can choose to operate fully or partially in the legal or in the illegal sector, depending on the incentives provided by the State and the Mafia in terms of taxes and provision of public goods. Conversely, in our model the Mafia extorts firms independently of their legal status, under the threat of punishment for non-compliance, rather than following the promise of providing an informal service, and our empirical analysis focuses on legal companies, in particular on businesses that comply with the mandatory registration in official records such as those maintained by the Italian Chamber of Commerce.

Finally, the recent paper by Piemontese (2020) estimates the amounts of *pizzo* paid by firms in Northern Italy and its impact on resource misallocation. Differently from our paper, however, Piemontese (2020) does not observe actual *pizzo* figures. She employs a methodology that allows indirectly estimating sectoral averages under the assumption that *pizzo* is a linear function of revenues, therefore not considering within-sector heterogeneity of percentage *pizzo* payments as we do in this paper.

The paper is organized as follows: inn 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 analysis; in Section 7 we offer a discussion on the economics of extortion on the basis of our findings and draw our conclusions.

2. The dataset

As mentioned in the Introduction, one of the main contributions of this paper is the analysis a newly built dataset combining information on the exact amounts of money paid to the mafia with data from companies' 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 each case of extortion, 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 the data.[12] Overall, the extortion database contains information on approximately 2300 episodes of extortion but the exact amount of *pizzo* is only reported for a subset of cases.

For this paper we extracted all episodes from the original database 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

[6] Our results are also more generally in line with the findings that corruption and bribes of public officials, another characteristic of economies with low institutional quality, have a disproportionate negative effect on small and young businesses (Seker and Yang, 2014) and on new entrants rather than on incumbents (Couttenier and Toubal, 2017). See also Amodio et al. (2022) for theory and empirical evidence on how to design an incentive scheme for tax inspectors in order to reduce bribe payments.

[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. 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 with data from businesses' financial statements and to the best of our knowledge it represents the first dataset of this type. In fact, other empirical analyses of sensitive topics such as extortion and corruption 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).

[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 neighboring Mafia families. According to Paoli (2003, p. 45) a mandamento is: "a district incorporating an average of three mafia families". These families elect their own head, named "capo mandamento".

[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 companies 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 is the year of *pizzo* payment that we will consider in our analysis. As such, the "year" of payment should be considered as merely indicative of the period in which the payment was made, but it can still provide a further control in the econometric analysis.

[11] Payments to the Mafia are made on a monthly basis, two or 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] Specifically, excerpts from relevant court documents and the name of the police operation/investigation the documentation originates from.

amount paid.[13] With respect to this subset, we were able to match information on the extorted company with data in 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 company data from CCIAA (i.e., legal form, first year of activity, initial capital, number of employees, number of local units, information on whether the company is still active at the date the data were collected).[17] For limited liability firms only we collected the financial statements available in the period 1992–2011.[18] We did not find any financial statements for 14 of the 134 matched limited liability companies.[19]

Our final sample therefore consists 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 the CCIAA except financial statements. For limited liability companies, we have 120 firms with the same data on *pizzo*, plus financial statements. This subsample will be the main focus of our analysis, although we will consider data from partnerships for a robustness test. 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 when the financial statements were available. Unfortunately, we do not have sufficient information on time variation of *pizzo* in the data to perform this type of analysis. Therefore we chose to average the financial statement data over the available years and perform a cross-section analysis.

The obvious shortcomings of this dataset are that: (i) the sample of *pizzo* episodes comes from judicial sources and as such it is non-random; (ii) the sample is small. As for point (i), ideally it would be appropriate to consider a random sample from the population of the extorted firms that, however, is not observable because of the illegal nature of extortion.[20]

As pointed out in the literature on the empirical analysis of criminal cases (see, e.g., Zatz and Hagan, 1985), a sample coming from judicial sources may suffer from different types of bias. First and foremost, the cases may originate from complaints of the victims and in our case this could depend on one of our critical variables, firm size. For example, if small businesses are more heavily taxed by the Mafia (as we show in this article) they may be more likely to complain. However, we believe that self-reporting is a minor issue for our sample, irrespective of company size. The cases of *pizzo* in our dataset appear in judicial documents as part of the evidence found during investigations and come from various sources, among which *pizzini*, i.e. small pieces of papers that mafiosi use to communicate, accounting books maintained by the gang members, state witnesses' confessions, etc. These large investigations often have origins from efforts to eradicate the criminal organization itself rather than from specific complaints from victims. While we cannot completely rule out that investigators at some point received confidential complaints from victims, notifying authorities of extortion has historically been a rare phenomenon (see, e.g. Calderoni, 2011, p. 52, on the under-reporting of extortion cases) as it exposes entrepreneurs to a severe risk of retaliation (Sicilians vividly remember the case of Libero Grassi, a businessman who reported the racketeers and was subsequently murdered).

Other selection issues can originate from the way investigations are conducted. Variation in law enforcement, broadly defined, can affect the probability that extortion cases are found by courts. For example, court efficiency may vary geographically, investigation efforts can be addressed towards some specific types of companies following prosecutors' strategies and their discretionality. While we cannot address distortions stemming from unobservable characteristics of the investigation process, we can take into account possible biases that can be linked to some observable factors. The two variables that we can consider are the province and the sector of the firms in our sample.

Figs. 1 and 2 present the provincial and sectoral distribution of the observations in our sample.

From Fig. 1 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.[21] Fig. 2 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".

In Appendix A we compare the distribution of observations in our sample with the distribution of Sicilian firms by province and sector, and show that in our sample there is an over-representation of firms in provinces where the Mafia is stronger, such

[13] As mentioned, other observations for which the amount of *pizzo* is recorded refer to annual and one-off payments (156 and 327 respectively). At the time of data collection, however, financial statement data on firms that paid annual or one-off pizzo were not available. The analysis of these different types of payments will be the subject of future research.

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

[15] Eleven observations refer to companies for which multiple cases of extortion were reported.

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

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

[18] Only this type of company is required by Italian law to file a copy of the financial statements with the local Chamber of Commerce.

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

[20] This is especially true for extortion by a criminal organization such as the Sicilian Mafia, which is strictly devoted to secrecy and requires obedience to its code of *omerta*' (Gambetta, 1993, p. 121).

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

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

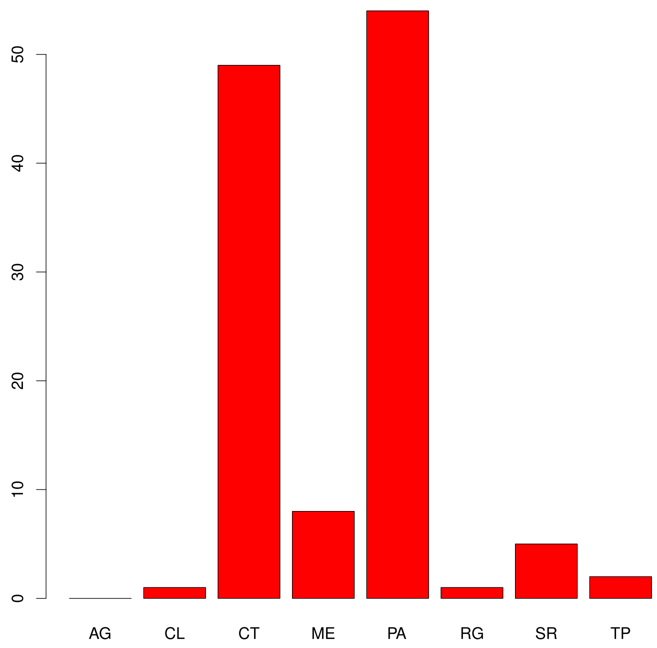


Fig. 1. Distribution per province.

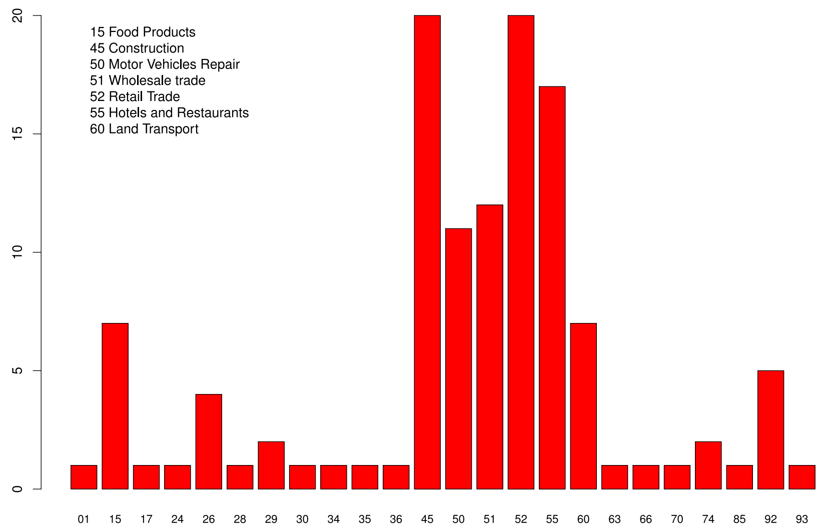


Fig. 2. Distribution per sector.

as Palermo and Catania, and in the sectors more vulnerable to Mafia extortion, for example low-tech sectors. Taken at face value, this would be evidence that our sample is a good representation of the extortion market. However, we cannot rule out that the distribution in our sample partly reflects variation in law enforcement by sector and by province. For example, in provinces where more firms are active (i.e. Palermo and Catania, see Table 6) investigators might devote greater efforts to fighting extortion rather than prosecuting other crimes, or larger sectors might be considered more important by prosecutors to be cleared of Mafia predation. To take this possibility into account, in the econometric analysis we will use a weighting scheme with weights defined as the inverse of the probability of appearing in a sample from judicial documents, as proxied by the shares of firms in provinces and sectors (see, e.g., Mastrobuoni and Patacchini, 2012, p. 32–33, for a similar approach in an analysis of criminal social networks when data on individual *mafiosi* come from investigation files).

Finally, to deal with the issue of the small sample size, we also consider a larger sample by including data on partnerships that contain a measure of firm size (the number of employees) comparable to the one for limited liability companies. This increases the number of useful observations to 240. Appendix E.3 contains the details and the results, which are consistent with those in the main text.

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

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

3. *Pizzo* and firm characteristics: stylized facts

In this section we present a preliminary analysis aimed at establishing some stylized facts on 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 each firm we will consider the relationship between the recorded *pizzo* value and: (i) firm sector and, (ii) average values of measures of firm size, where averages are calculated using the data available for each firm.[23]

The mean *pizzo* value and standard deviation in our sample of 120 observations amount to €689 and €1,313. By deleting a strikingly high value of approximately €14,000, we obtain a value of mean and standard deviation of €577 and €490. However, there are remarkable differences across sectors. Table 1 reports the *pizzo* averages for the most represented sectors.

The highest value is found in the Construction sector, and the lowest in the Wholesale Trade. The highest *pizzo* value was paid by a firm in the Construction sector: deleting this outlier significantly reduces the sector average below that of the Land Transport sector.[24] Some of these differences, in particular when comparing the highest *pizzo* values to the others, are statistically significant.[25]

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

It is apparent from Fig. 3 that the relationship between *pizzo* and 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. Fig. 4 contain the scatterplots of the relation between *pizzo* values and size (measured by total fixed assets) for a sector exhibiting a positive relation (Construction) and for a sector exhibiting a flat relation (Hotels and Restaurants).

In the case of Construction the estimated elasticity is 0.11 (p-value: 0.07) while for Hotels and Restaurants (and for all the other sectors, with the exception of Land Transport) the estimated elasticity is never significantly different from zero, implying that the Mafia sets a flat "tax" schedule.[29] To sum up, we identified the following stylized facts on the relation between the level of *pizzo*

[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 2, most of the years that we associate with 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 company characteristics from financial statements' data, one should only consider financial reports for years not subsequent to the year of payment. However, the reports available 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 *pizzo* observations refer to the early 1990s, 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. However, if we compute the correlation of the financial statement 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 well proxied by the values computed by averaging after the year of payment.

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

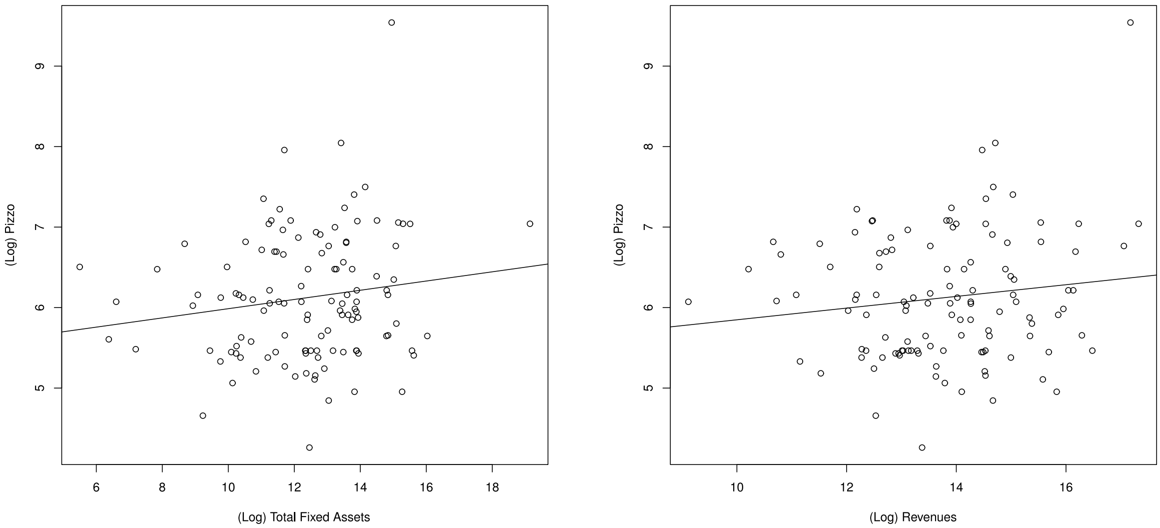
[25] Specifically, when all observations of *pizzo* in the sectors indicated in Table 1 are considered, a one-way Anova test rejects the hypothesis that the sectoral means are different, while pairwise Welch tests (that do not assume equality of variances across sectoral observations) reject the null hypothesis of equal means at 10% significance level when average *pizzo* in the Construction sector is compared to Food Products and Wholesale Trade. Differently, when the highest *pizzo* is excluded, the one-way Anova test rejects the null hypothesis of equal means at 5% significance level, in particular for the pairwise significant difference (according to the Tukey HSD test) between average *pizzo* values in Construction and Hotels and Restaurants (at 10% significance level) and Wholesale Trade (at 5%). Pairwise Welch tests confirm this results (at 1% significance level) and reject the null of equal *pizzo* means also in a comparison of Construction with Motor Vehic. Repair (at 5% significance level) and Food Products (at 1%).

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

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

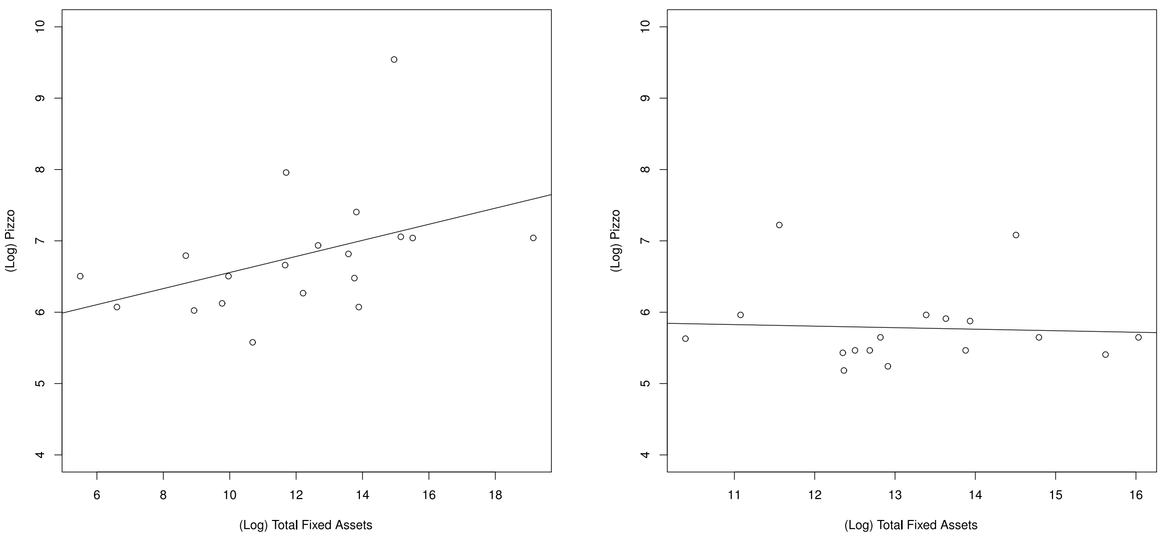
[28] Removing the highest *pizzo* has negligible consequences on the estimated bivariate relationship. Fig. 16 in Appendix E.1 reports the scatterplots of the relation of *pizzo* with two alternative measures of size, related to the workforce: the number of employees and the amount of personnel costs. The estimated bivariate relationships are very similar to the ones in Fig. 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 a proxy for size, Motor Vehicles Repair also 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) *Pizzo* and Total Fixed Assets (b) *Pizzo* and Revenues

Fig. 3. The relation between the amount of *pizzo* and measures of firm size: total fixed assets and revenues.



(a) Construction (b) Hotels and Restaurants

Fig. 4. *Pizzo* and Total Fixed Assets, sectors with positive and flat relations.

set by the Mafia and firm sector and size: (1) the amount of *pizzo* varies significantly across sectors; (2) the amount of *pizzo* varies slightly with the size of the firm. Stylized facts (1) and (2) can be reconciled by stylized fact: (3) the elasticity between *pizzo* and size varies across sectors, being moderately positive or nil.

In Sections 4 and 5 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 business so as to maximize its profits.[30] Firms are heterogeneous. There is a continuum of potential firms indexed by a productivity parameter θ distributed on the interval $[\theta_l, \theta_h] \subseteq \mathbb{R}_+$ according to a smooth cumulative distribution function $G(\theta)$ with strictly positive density $G'(\theta) = g(\theta)$. We assume that the distribution satisfies the monotone hazard rate property, so that $H(\theta) = (1 - G(\theta))/g(\theta)$ is decreasing. Firm profits gross of any amount forced to pay the Mafia are $\theta f(k) - rk$, where k is a choice variable for the firm meant to broadly represent its size. If a firm opens for business it chooses $k > 0$, while if it stays out $k = 0$. The function f is smooth, strictly increasing, strictly concave and satisfies the Inada conditions $f(0) = 0$, $f' \to \infty$ as $k \to 0$ and $f' \to 0$ as $k \to \infty$. 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 type to choose the efficient level of size, i.e., the one that maximizes gross profits, and then set the extorted amount exactly equal to these 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 the extortion to the size of the firm.

The timing we have in mind is the following. The presence of Mafia is common knowledge among firms, as it is its ability to make irrevocable and non-negotiable offers. However, the Mafia does not know θ, and it cannot 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 that has chosen k, under the promise of a punishment z to be inflicted on a non-compliant firm. We assume that Mafia has enough reputation concerns that it always finds it optimal not to renegotiate the extortion in case of compliance and to inflict punishment on a non-compliant firm.[31] Firms know both $x(k)$ and z when choosing whether to open for business. Once in the market, they choose the optimal amount of observable k 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. The 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 comply, in which case it pays $x(k)$, or to not comply, in which case it pays the cost z.

In the following sections our goal will be to theoretically characterize the optimal choice of the extortion function $x(k)$ and to compare it with the empirical counterpart in our dataset.[32]

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 the equilibrium *net profits* of the firm: $\pi(\theta) = \theta f(k(\theta)) - rk(\theta) - x(\theta)$. We will then recover the indirect mechanism $x_*(k)$ that implements the optimal choice. This will be our theoretical *pizzo function*.

We begin the analysis with the compliance choice of the firm in stage 5. It is clear that the firm will choose to be compliant with extortion if $x(\theta) \le z$, which will be satisfied for every θ by z large enough. In this section we assume a strong Mafia, so that the amount of firepower is large enough that the Mafia is never constrained in the choice of pizzo. In Appendix D we extend the model in two directions, by allowing the punishment to be a fraction of firm's size, up to a fixed upper bound, and by assuming a weak Mafia, which is effectively constrained in the choice of extortion by its own inability to punish firms harshly, and show that the main theoretical implications of the model are confirmed, in particular the shape of the *pizzo* function. In stage 4, anticipating compliance

[30] As pointed out in Footnote 2, while more than one family can rule over a *Mandamento*, their coordination implies that no conflicts or competition in fact exist among the families in any given territory so that each individual firm deals with a subject acting as the sole authority over the territory the business is located in.

[31] As pointed out in detailed descriptive studies of extortion carried out by the Sicilian Mafia such as Scaglione (2008), the process leading to the settlement of the amount of *pizzo* may appear to be a bargaining process, in which the Mafia sets an initially high request that is then reduced until it is accepted by the firm. However, this strategy is more related to the strategy of the Mafia to be perceived as a benevolent institution, able to understand and meet the requirements of the business. Given the disproportionate difference in bargaining power between the Mafia and the individual company, what seems to be a negotiated fee is actually a take-it-or-leave-it offer.

[32] In Appendix A we explain why, in line with Schelling (1971), businesses 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 it cannot observe the signals that are correlated with profits, such as k or the distribution of θ.

in equilibrium, the firm optimally chooses k, which in this context amounts to incentive compatibility. Since the profit function of the firm satisfies single crossing it is standard to verify that incentive compatibility is satisfied if and only if $\pi'(\theta) = f(k(\theta))$ and $k'(\theta) \geq 0$.[33] Again anticipating future decisions, in stage 3 a firm will decide to enter the market if $\pi(\theta) \geq 0$, since the outside option is independent of firm type. These points allow the optimization problem of stage 2 of the Mafia to be written in the following compact form:

$$\max_{k(\theta),\pi(\theta)} \int_{\theta_l}^{\theta_h} (\theta f(k(\theta)) - rk(\theta) - \pi(\theta))dG \tag{mp}$$

$$s.t. \quad \pi'(\theta) = f(k(\theta))$$

$$\pi(\theta) \geq 0,\ \theta f(k(\theta)) - rk(\theta) - \pi(\theta) \leq z,\ k'(\theta) \geq 0.$$

The solution is found by applying standard techniques in contract theory and assumes that the Mafia is strong enough that the firm always prefers to pay extortion instead of suffering the punishment.[34]

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) $(\theta - \frac{1-G(\theta)}{g(\theta)})f'(k_{mp}(\theta)) = r$ if $\theta \geq \frac{1-G(\theta)}{g(\theta)}$, $k_{mp}(\theta) = 0$ otherwise;

(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) The optimal solution can be implemented via a strictly concave extortion function $x_*(k)$. If in addition $f(k)$ is homogeneous of degree $\alpha \in (0,1)$ and $H(\theta)$ is convex then $x_*(k)/(\theta_{mp}(k)f(k) - rk)$ is strictly decreasing.

In our model, firms are heterogeneous in terms of the productivity parameter θ, which measures how they 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: $\theta f'(k) = r$. Moreover, it would choose extortion exactly equal to gross profits, so that $\pi(\theta) = 0$ 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 the Mafia tailoring the *pizzo* of stores to the number of shop windows facing the street.[35] 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 making 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 ($G(\theta_h) = 1$). Moreover, for very low-θ types the inefficiency might be extreme: the Mafia might choose a tariff so that they are left out of the market.

The intuition for this result comes from the effect of asymmetric information on the value that the Mafia attaches to type θ opening and running a business. From the expression of net profits in point (ii) we know that the rent left to a type θ is increasing in the choice of size of all lower types, a consequence of the envelope condition that characterizes incentive compatibility.[36] In other words, increasing the size of type θ increases net profits of all types above, of which there are $1 - G(\theta)$. This is a cost for the Mafia as the rent left to firms is from its perspective money left on the table. The benefit of increasing size is of course that type θ itself produces more profits to be expropriated, and there is a measure $g(\theta)$ of these firms. Therefore the presence of asymmetric information decreases the value of type θ by the ratio $H = (1 - G)/g$, which indeed measures the cost over benefit of having type θ participating.[37] Compared to first best, this generates an inefficiency through lower-than-optimal firm size for almost all firms.[38]

33 Nonetheless we prove it formally in Appendix C.

34 The proof is in Appendix C.

35 Scaglione, 2008, p. 150, provides anecdotal evidence on this.

36 See Lemma 2 in Appendix C.

37 Incentive compatibility requires that size must preserve the same monotonicity of the perfect information solution, namely size must be increasing in productivity. This is obtained by assuming the monotone hazard rate property, in particular that H is decreasing, so that the virtual type $\theta - H(\theta)$ is increasing in the true type. Intuitively, this assumption rules out situations where the cost of asymmetric information increases so much with type, so that it becomes large enough that the Mafia would want to distort size more for larger types than for lower types, which would violate incentive compatibility. A sufficient condition for H decreasing is log-concavity of the density function, a property that is shared by many commonly used distributions (Bagnoli and Bergstrom, 2006).

38 Descriptive evidence suggests that, indeed, firm size in Sicily is on average particularly small. For example, Lavezzi (2008, p. 208–9) reports data from ISTAT showing that in 2001 in Sicily approximately 81% of businesses had one or two employees, compared to a corresponding percentage of 75% for Italy, 78% in other Southern regions where organized crime is not pervasive (Abruzzo, Basilicata, Molise and Sardinia), and of 74% in Lombardy, one of the most developed Italian regions. At the same time, the share of companies with more than 100 employees amounted to 10% in Sicily, 21% in Italy, 15% in Abruzzo, Basilicata, Molise and Sardinia, and 41% in Lombardy. See Lavezzi (2008, p. 208–9) and STAT (2021, p. 24) for more recent evidence of the small size of firms in Southern Italian regions.

Crucially for our empirical exercise, point (iii) shows that the Mafia induces the desired level of investment by using a strictly concave extortion function. The Mafia is able to discourage excessive underinvestment of more productive firms by imposing a larger *marginal pizzo* at smaller investment levels, so that the marginal pizzo ends up decreasing in size. Finally, from point (ii) we see 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 ($\pi_{mp}(\theta_l) = 0$ and $\pi_{mp}(\theta) > 0$ for all $\theta > \theta_l$). Thus the Mafia fully expropriates profits of the lowest productive firm setting extortion equal to gross profits for this firm, while setting extortion lower than gross profits for more productive firms. At the very bottom of the distribution this implies that the fraction of profits expropriated by the Mafia is locally decreasing in size, and the second part of point (iii) extends this property monotonically to the whole set of sizes that we observe in equilibrium under some mild technical assumptions.[39]

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 Section 6.1 we apply the functional form

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

to our dataset and test whether $0 < \alpha < 1$.[40] The second is that the incidence of the pizzo on profits should be larger for smaller firms. In Section 6.2 we measure the incidence of the *pizzo* with the fraction of operating profits appropriated by the Mafia, the *pizzo rate*, and we test whether it decreases with firm size.

6. Econometric analysis

In this Section we perform 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 their financial statements.

6.1. Estimating the pizzo function

In this section we provide an econometric analysis of the relation between the *pizzo* paid by the firms in our sample and firm 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.[41]

We estimate Eq. (1) with OLS as well as with WLS. As noted in Section 2 and 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 1995–2006.[42] Table 2 reports the results.

The estimated elasticities in Table 2 take on significant values comprised between 0.08 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 dummies also seems to exert a non-negligible effect, in particular by decreasing the estimated values of the elasticities.[43] We note that all coefficients in Table 2 are strictly less than one, which implies a strictly concave relationship between *pizzo* and size, as our model predicts.

We conducted some robustness tests on the results in Table 2. First of all, we ran the regressions of Table 2 excluding the observation on the highest *pizzo*, treated as an outlier.[44] Table 9 in Appendix E.2 shows 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 for most

[39] At point (*iii*) of Proposition 1, convexity is taken in a weak sense, so that a constant or linear H satisfies the assumption. The parametric formulation in Appendix C is an example that satisfies all the assumptions.

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

[41] As noted in Section 2, the original dataset included information on the *Mandamento* (see Footnote 2) where the extorted business is located. However, the paucity of the data prevents the consideration of this piece of information. The identification of different Mafia "taxation" policies by *Mandamento* remains an interesting topic for future research.

[42] The population of firms considered corresponds to the active joint-stock companies in Sicily. The source of data is the *Movimprese* database (https://www.infocamere.it/movimprese). The 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.

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

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

Table 2
Pizzo and 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***
	(0.830)	(0.479)	(0.778)	(0.659)	(0.506)	(0.717)
Total Fixed Assets (log)	0.054*	0.091***	0.080***	0.046	0.138***	0.112***
	(0.031)	(0.033)	(0.029)	(0.036)	(0.037)	(0.034)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

specification. In addition, we considered alternative measures of size. When considering revenues, the magnitudes and significance of the estimated coefficients are largely consistent with those obtained using total assets (see Table 10 in Appendix E.2) When considering the two measures of workforce size – personnel costs and number of employees – with the former measure the results are consistent with those based on total assets, while with the latter we find a positive and significant coefficient in two models out of six (see Tables 15 and 16 in Appendix E.2). The drawback of using the number of employees is that such data are not updated over time, as the figure is included in the annual financial statements from which we extracted the other measures of size.

However, as noted, data on the number of employees are also available for partnerships.[45] This allows us to increase the sample, using data on both limited liability and partnerships. Appendix E.3 contains the results of regressions on such extended sample, with the number of employees as the measure of size. Results are largely consistent with those of the main text.

In Section 3 we showed that, in bivariate regressions, there are 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 positive slope such as Construction (as shown in Fig. 4) and Land Transport. Therefore the equation to be estimated becomes:

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

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

Table 3 shows that, especially with WLS estimations, there appears to be 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 (the sum of the estimated coefficients in Models (5) and (6)). Results in Table 12 in Appendix E 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 for this finding. One relies on the extensive knowledge that organized crime has of companies in some sectors, for example the Construction sector, allowing for control of operations and thus a better discrimination of firms' ability to pay.[46] The 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.[47]

[45] For both limited liability firms and partnerships the number of employees might appear in other documents retrieved from the CCIAA, that refer to various events happening during the life of a business, such as its founding, changes in ownership, etc.

[46] "Mafia organizations entirely control the building sector in Palermo - the quarries where aggregates 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 (2008).

[47] 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 Eq. (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.

Table 3
Pizzo and 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***
	(0.712)	(0.522)	(0.791)	(0.633)	(0.522)	(0.811)
Total Fixed Assets (log)	0.040	0.057	0.045	0.050	0.100**	0.075*
	(0.026)	(0.039)	(0.035)	(0.035)	(0.040)	(0.040)
Total Fixed Assets (log) x D	0.048***	0.073	0.072	0.028	0.191**	0.175*
	(0.014)	(0.067)	(0.054)	(0.017)	(0.089)	(0.095)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

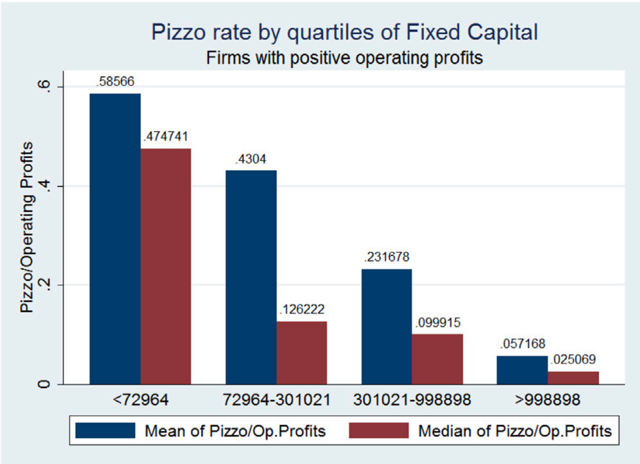


Fig. 5. *Pizzo* rate and Total Fixed Assets: mean and median values per quartile.

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 each euro invested in the size of the firm decreasing as size increases. A further question, which is still unsettled in the literature, is what the actual fraction of gross profits paid as extortion is, and how this percentage is correlated with size. In other words, we want to measure the degree of progressivity of Mafia “taxation”.

For this purpose, we compute the average *pizzo rate*, given by the ratio of *pizzo* to the operating profits of the firms,[48] and evaluate it as a function of the size of the firm. Figs. 5–8 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 Figs. 5–8 we note that the incidence of the *pizzo* strongly decreases with the size of the firm, starting from very high

[48] This value refers to the difference between revenues and production costs. It abstracts, therefore, from other costs, such as interest, and from taxes. As such, it provides the “purest” measure of the profits from the normal business of the company. We compute the rate for firms in our sample having positive average operating profits in the period of observation.

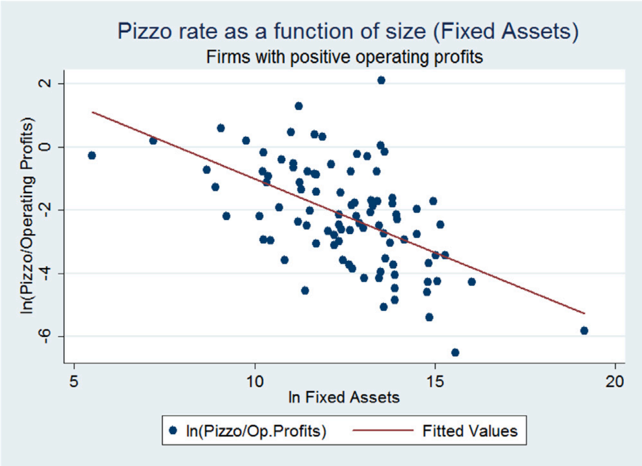


Fig. 6. *Pizzo* rate and Total Fixed Assets.

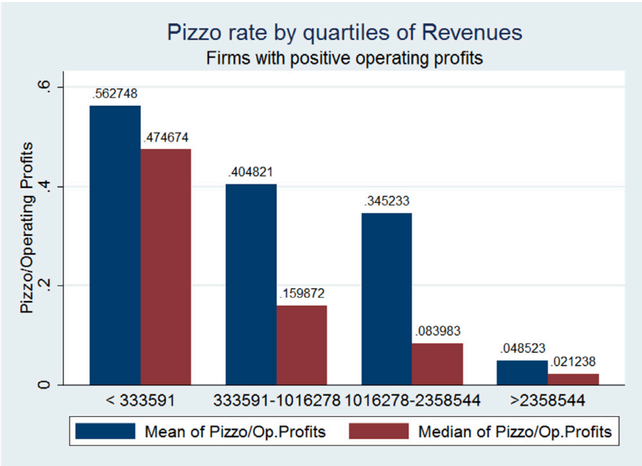


Fig. 7. *Pizzo* rate and Revenues: mean and median values per quartile.

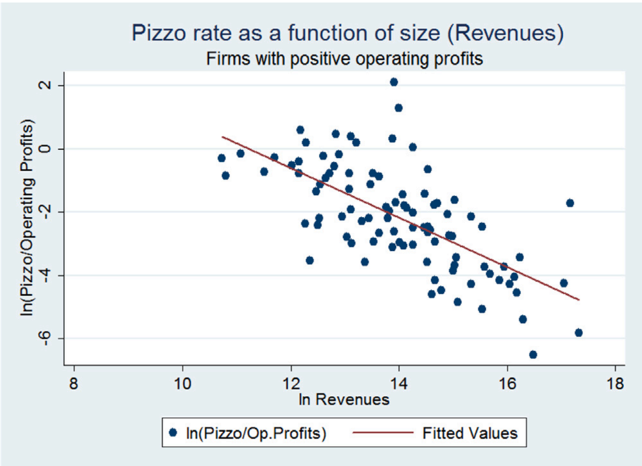


Fig. 8. *Pizzo* rate and Revenues.

Table 4
Pizzo Rate and Total Fixed Assets (OLS and WLS).

	Dependent variable:					
	log (pizzo rate)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.248	2.217*	1.705	−0.335	2.194	1.863
	(1.198)	(1.179)	(1.419)	(1.643)	(1.633)	(1.596)
Total Fixed Assets (log)	−0.498***	−0.475***	−0.529***	−0.516***	−0.490***	−0.614***
	(0.068)	(0.080)	(0.083)	(0.086)	(0.111)	(0.079)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

values for the smallest firms.[49] Table 4 presents the results of OLS and WLS regressions of the *pizzo rate* on total fixed assets, with the same set of control dummies we used in the previous section. The results confirm that the relationship is significantly negative: it is not driven by province, sector or time differences.[50]

This exercise allows us to quantitatively assess the relevance of extortion on 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 companies 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 of 2%, as the largest firms are "taxed" for only approximately 2% of their operating profits.[51] Overall, we find clear evidence that *Mafia taxation is regressive*.[52]

6.3. A comparison with state taxation

In the previous section we saw 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 that strongly decreases with firm size. In this section we compare the "taxation" imposed by organized crime with the one imposed by the official institution in charge of taxing companies and people: the State.

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

The results in Table 5 show that the structure of State taxation is remarkably different from that of organized crime: the estimated elasticity is much higher, taking on values approximately between 0.58 and 0.63. Since we are estimating constant elasticity functions, we can take the distance between the estimated elasticity and 1 as a measure of how regressive the system is, 1 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.[53] 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

[49] In the left panel bar charts 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 company 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.

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

[51] We cannot rule out that part of the difference in the pizzo rate between small and large firms is determined by a larger fraction of hidden revenues (and profits) among small firms, although the theoretical literature on the issue also mentions reasons for larger firms to hide more. For example, larger firms being involved in more complex operations might have more opportunity to conceal profits (Slemrod, 2007, p.32). We believe, however, that the difference is too large to be entirely due to differences in reporting compliance. Unfortunately, we are not aware of estimates of revenue reporting compliance by firm size for Sicily. Data in Gatti and Honorati (2008, Table 2) for a sample of firms in developing countries show that micro firms (1–9 employees) report on average 72% of sales, while large firms (more than 250 employees) report on average 87% of sales. Assuming that these percentages are also good approximations of underreporting of profits in our data, we would obtain, for example, that firms in the lowest quartile of the distribution of fixed capital face incidence on true profits equal to (0.47*0.72)*100 = 28% while the incidence for larger firms would be (0.87*0.025)*100 = 2.2% (using for each class size the median in Fig. 5).

[52] In order to use a larger number of observations we considered a robustness check based on the following hypothesis: some relatively large values of the *pizzo* rate may characterize firms with negligible profits. As such, these profit levels might not be very different from the negative profits characterizing the firms excluded from the analysis. For these reasons, we can consider as a robustness check an analysis in which any firm for which either the pizzo is larger than profits or the profits are negative is assigned a value of 1 to its *pizzo* rate. Table 17 in Appendix E.2 contains the results of this robustness test, which are in line with those of Table 4.

[53] Table 14 in Appendix E.2 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 businesses.

Table 5
Taxes and 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
	(1.091)	(1.096)	(1.363)	(1.377)	(1.498)	(1.680)
Total Fixed Assets (log)	0.578***	0.575***	0.594***	0.624***	0.632***	0.593***
	(0.073)	(0.083)	(0.085)	(0.085)	(0.115)	(0.094)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

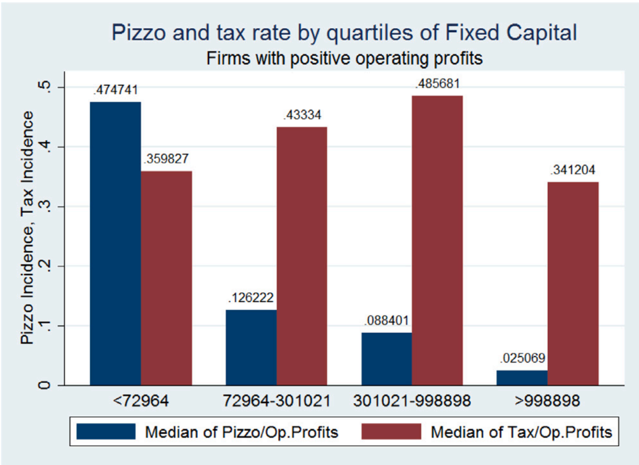


Fig. 9. *Pizzo* and Tax rate by Total Fixed Assets: median values per quartile.

total taxes paid by the firm for the year, which is then averaged across years in the sample. For consistency 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 Figs. 9–12.

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.

It is clear that the two rates behave differently as a function of size. While the *pizzo* rate is strongly decreasing, the tax rate remains constant or increases slightly as size increases, averaging approximately 40% of operating profits. We note that firms in the smallest quartile of our sample are particularly burdened by the combined effect of State taxes and *pizzo*. If one takes operating profits as a measure of the value added produced by a company, 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 businesses.[54]

[54] The analysis of Section 6.2 is carried out considering profits before taxes. In this section, however, we showed that State taxation is a non-negligible share of company profits. Therefore, as a robustness check, we considered the relationship between the *pizzo* rate and firm size computed on *after-tax* profits. In Appendix E.2 Table 18 contains the results, while Table 19 contains the results when *pizzo* rate = 1 for firms with negative profits and for firms with pizzo rate > 1. In both cases results are consistent with those in the main text.

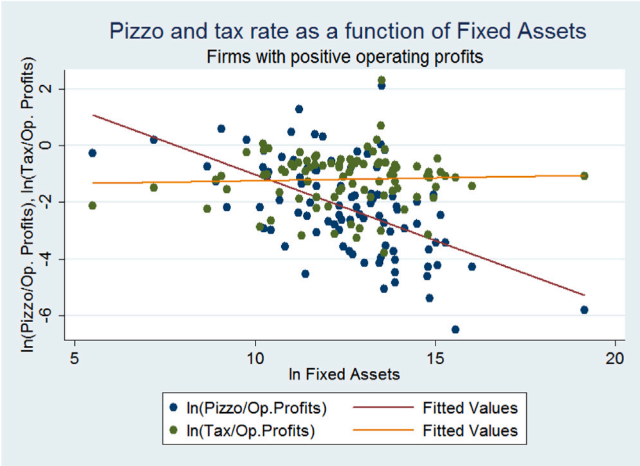


Fig. 10. *Pizzo* and Tax rate by Total Fixed Assets.

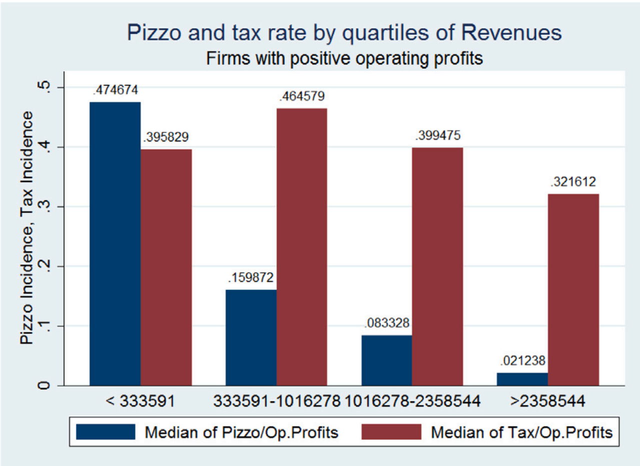


Fig. 11. *Pizzo* and Tax rate by Revenues: mean and median values per quartile.

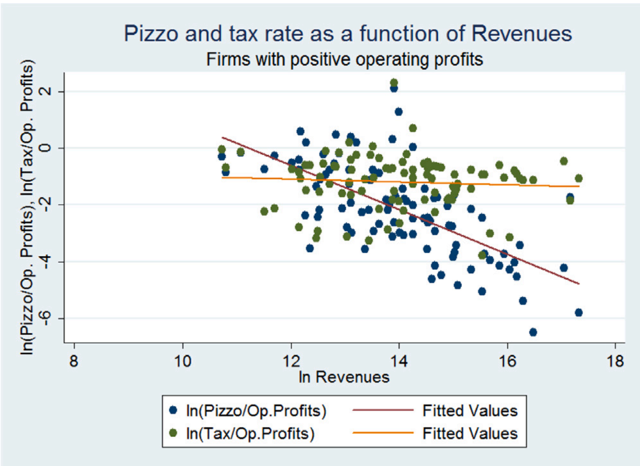


Fig. 12. *Pizzo* and Tax rate by Revenues.

7. The economics of extortion: concluding remarks

In this paper we presented a theoretical and empirical analysis of the extortion of firms operating in legitimate sectors by one criminal organization, 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 business 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, increasing rapidly at small scales and becoming somewhat flat at larger scales.[55] For companies operating at small scales this extra cost 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 also have also implications for the dynamics of development. An important source of growth for firms, be 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 less productive. The two effects combine to diminish the amount of resources available for reinvestment, thus hampering the potential for company growth. Another important source of business growth is access to external funds, namely bank loans. This channel is also affected by the presence of organized crime. In the case of Italy there is evidence that in the presence of crime, and in particular of organized crime extorting businesses, interest rates on banks loans are higher, the effect being driven mainly by the increase in the interest rate spread on smaller companies. Moreover, firms are required to put up more collateral and they are credit rationed.[56] Our findings shed light on the possible mechanism at play. Conditioning on individual characteristics, in areas dominated by organized crime smaller businesses are extorted more, so they end up being less profitable and limited in their ability to build up enough collateral to access further credit. Thus they end up being credit rationed and paying higher interest on bank loans.

These considerations point at the possibility that an economy where organized crime systematically imposes extortion on legitimate businesses may fall in a low-growth poverty trap.[57] 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 burdened by 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 Galor and Zeira (1993) and 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 growth model for an economy plagued by extortion under asymmetric information and evaluating its empirical content is an interesting topic for future research.

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 to evaluate its possible biases. In particular, in Appendix 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 Appendix A.2 we analyze two observable characteristics of the firms in the sample, their province and sector, and compare them with the provincial and sectoral distributions of Sicilian firms.

A.1. From the original sample to our sample

In Fig. 13 we compare the distribution of the 488 (unmatched) observations on monthly *pizzo* to the distribution of 334 observations of the matched firms.[58] Fig. 13 shows that the distribution of the smaller set of 334 observations does not display remarkable differences, so that the deletion of the observations of the unmatched firms does not seem to bias the sample.

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55 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.

56 See the empirical estimates in Bonaccorsi di Patti (2009).

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

58 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).

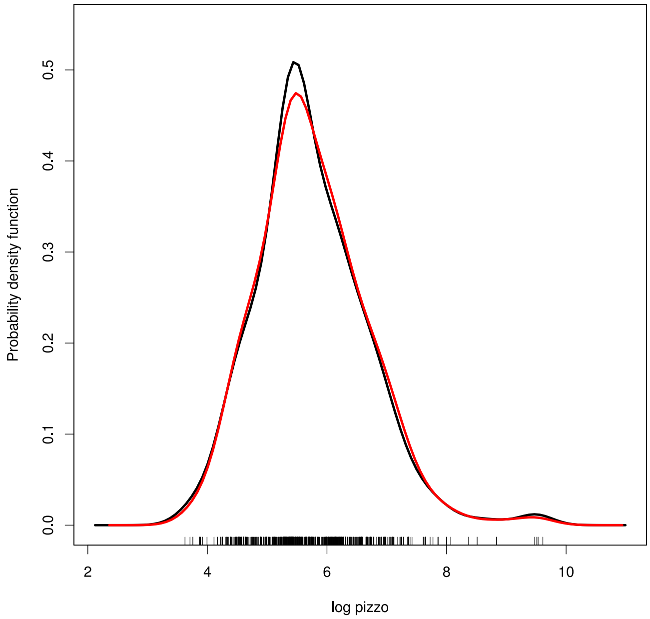

Fig. 13. Distribution of (log) *pizzo* values: all observations on monthly *pizzo* (black) vs values for matched firms (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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

	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

A.2. On the provincial and sectoral distribution of sample data

In Section 2 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 nonetheless possible 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, then 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 the *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.

Table 6 compares the provincial distribution of observations in our sample with the provincial distribution of all firms.[59]

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 the Mafia is particularly strong in the provinces of PA and CT so that in these provinces a higher proportion of firms is extorted than the overall share of Sicilian firms, while in the other provinces the share of extorted companies is lower than the regional share. Is this actually the case? A survey carried by a major Italian business association Confesercenti (2008, p. 12) 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

[59] 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 period of interest is 20652, so that the size of our sample is 0.58% of the population.

Table 7
Indicators of Mafia presence at the provincial level.

	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

80%, while in provinces such as EN, SR and RG it is the lowest.[60] The over-representation of the provinces of Palermo and Catania in the sample is therefore consistent with this evidence.

As a further check, we compare the distribution of sample observations to the distribution of measures of Mafia penetration at the provincial level, under the hypothesis that where the Mafia is more pervasive, more businesses are extorted. Calderoni (2011) discusses the measures of Mafia penetration existing in the literature and proposes new ones. In general, these indicators are constructed by considering data on mafia-related crimes (including extortion), other indicators on the presence of the mafia (e.g. confiscated properties), or other socio-economic indicators.[61] Since this type of measurement necessarily involves some degree of 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.[62]

For ease of comparison, the order of the provinces in Table 7 is based on the average ranking of provinces in the indices presented.[63] 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, our sample might under-represent the extorted businesses of the province of Caltanissetta (CL).

Now we highlight the characteristics of the sectoral distribution of the observations in our sample. In Fig. 2 we reported the sectoral distribution of the sample observations, showing that some sectors appear more frequently than others. Following the argument we proposed for the provincial distributions, in Fig. 14 we compare the sectoral distribution of the sample with the sectoral distribution of the Sicilian firms.[64]

Fig. 2 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 Fig. 14 shows that most of these sectors are over-represented in our sample with respect to the population shares, specifically: "Food Products", "Motor Vehicles Repair", "Retail Trade", "Hotels and Restaurants", and "Land Transport".

Along the same line of reasoning proposed for 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.

Indeed, Schelling (1971) argued that some characteristics of a company make it more vulnerable to penetration of organized crime through extortion. In particular, Schelling (1971) argued that it is easier for racketeers to extort businesses with more visible output or profits, since in this case company owners cannot hide their capacity to pay the *pizzo*. Furthermore, 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

[60] However, no exact measures of such differences are offered. The share of businesses actually paying *pizzo* is a so-called *dark number*, i.e. a number difficult to observe due the high under-reporting. See Asmundo and Lisciandra (2008) for further discussion for the case of extortion in Sicily.

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

[62] 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 seeks to measure 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 from 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 1980s to the interval 2007–2009. For further details and references see Calderoni (2011).

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

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

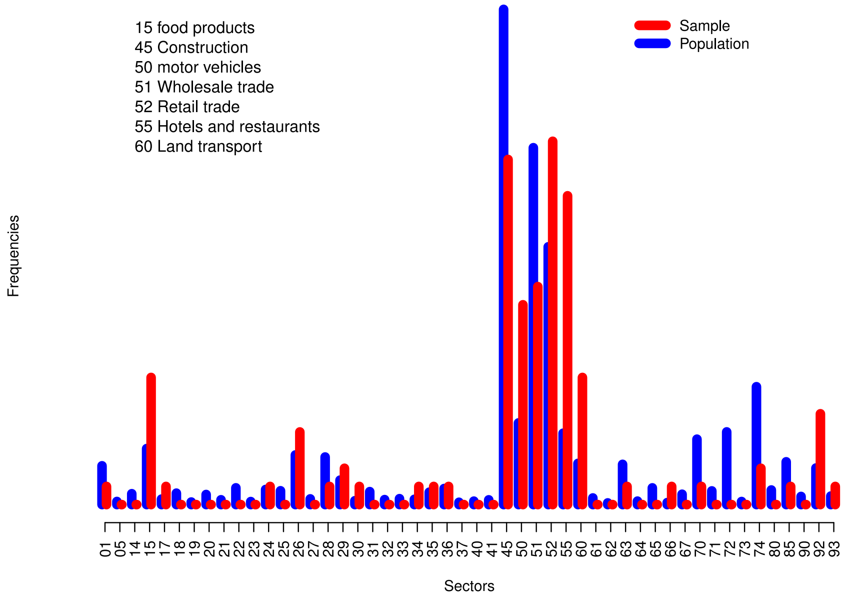

Fig. 14. Distribution of observations across sectors: our sample and population.

over-represented in the sample are characterized by a low technological level.[65] In fact, according to the EUROSTAT classification,[66] the "Food Products" sector is a "low-tech" sector, while the sectors of "Motor Vehicles Repair", "Retail Trade", and "Hotels and Restaurants" are "less-knowledge intensive" (LIS) service sectors.[67] The "Wholesale Trade" sector, which 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 helps 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.[68] The under-representation of "Construction" in the sample can be explained by the fact that the type of "pizzo" that is typically imposed on the businesses in this sector takes the form of one-off payments, which is made once the construction site is opened.[69] For the under-representation of "Wholesale Trade", we conjecture that such economic activities are less observable than, for example, retail trade. 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, based on the analysis carried out so far, we note that, with respect to the provincial and sectoral distribution of Sicilian firms, our sample contains a relatively high share of firms from the provinces of Palermo and Catania and from the sectors that the theory suggest are more vulnerable to extortion, or more tightly connected to the territory. As such, it can represent a good approximation of the extortion market. In any case, as discussed in Section 2, to take into account possible biases linked to the provincial and sectoral distribution of firms, in the 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.

Appendix 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,[70] while the sectors' technological level is based on the EUROSTAT definition.[71]

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65 Table 8 contains all details on the sectoral distributions.

66 See: http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

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

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

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

70 Available (in Italian) at: http://www3.istat.it/strumenti/definizioni/ateco/ateco2002.pdf.

71 See: http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

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.

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

Appendix C. Proofs for Section 4

Preliminaries

We first provide the technical details underlying the discussion leading to the formulation of (mp) and then the proof of Proposition 1.

In stage 2 the Mafia commits to an extortion function $x(k)$, which asks for payment x from a firm that chooses the level of capital k. This "offer" is observable by all potential entrants and it can be interpreted as the Mafia selling the permission of installing size k against the payment of extortion. It is without loss of generality to assume that the offer accepted by all firms, with the interpretation that a firm choosing $k = 0$ in effect decides to stay out of business paying no extortion. In principle the Mafia would like to adjust the offer according to the productivity type, but it does not have the information to do so, indeed it has to rely on the communication from the firm. It could put in place a general communication mechanism through which to elicit firms' types. The revelation principle states that in searching for the optimal mechanism it is without loss of generality to restrict attention to direct revelation mechanisms, that is functions $\{k(\theta), x(\theta)\}$ that depend on the revelation of the true type by the firm, that are incentive compatible, that is each

θ chooses the offer designed for itself.[72] As mentioned in the main text, it is more convenient to work with equilibrium net profits $\pi(\theta)$, the firm's rent, rather than transfers and then recover the transfer from the equality $x(\theta) = \theta f(k(\theta)) - rk(\theta) - \pi(\theta)$. The following lemma states necessary and sufficient conditions for incentive compatibility:

Lemma 2. *The direct mechanism $\{k(\theta), \pi(\theta)\}$ is incentive compatible if and only if $\pi'(\theta) = f(k(\theta))$ and $k(\theta)$ is increasing, so that a point of differentiability $k'(\theta) \geq 0$.*

Proof. Suppose $\{k(\theta), \pi(\theta)\}$ is incentive compatible and take types $\{\theta', \theta\}$ with $\theta' > \theta$. Each type prefers the offer designed for itself rather than the one designed for the other, that is

$$\pi(\theta) \geq \pi(\theta') + (\theta - \theta')f(k(\theta'))$$
$$\pi(\theta') \geq \pi(\theta) + (\theta' - \theta)f(k(\theta)).$$

which implies

$$(\theta' - \theta)f(k(\theta')) \geq \pi(\theta') - \pi(\theta) \geq (\theta' - \theta)f(k(\theta)).$$

Since f is strictly increasing, this implies $k(\theta') \geq k(\theta)$, so that $k(\theta)$ is increasing. Also, dividing all terms by $\theta' - \theta$ and letting $\theta' \to \theta$ we obtain $\pi'(\theta) = f(k(\theta))$. In the other direction, suppose $\pi'(\theta) = f(k(\theta))$ and $k(\theta)$ increasing but by contradiction the mechanism is not incentive compatible. Assume type θ prefers the offer designed for type $\hat{\theta} > \theta$, so that $\pi(\theta) < \pi(\hat{\theta}) + (\theta - \hat{\theta})f(k(\hat{\theta}))$. Therefore

$$\int_{\theta}^{\hat{\theta}} f(k(\hat{\theta}))ds = (\hat{\theta} - \theta)f(k(\hat{\theta})) < \pi(\hat{\theta}) - \pi(\theta) = \int_{\theta}^{\hat{\theta}} f(k(s))ds$$

which is a contradiction since f is strictly increasing and $k(\hat{\theta}) \geq k(s)$ for s in $[\theta, \hat{\theta}]$ since k is increasing. The contradiction for a deviation toward $\hat{\theta} < \theta$ is entirely analogous. ■

To find the optimal mechanism the Mafia chooses the offers $\{k\theta, \pi(\theta)\}$ to maximize expected payment under the incentive compatibility constraint, which by Lemma 2 reduces to $\pi'(\theta) = f(k(\theta))$ and $k'(\theta) \geq 0$, the participation constraint $\pi(\theta) \geq 0$ and the constraint that a firm in business always prefers to pay extortion rather than suffer the punishment.[73] These conditions lead to problem (mp), which in Proposition 1 we solve under the strong Mafia assumption that it has enough firepower to convince any firm in business to pay extortion rather than being punished.

Proof of Proposition 1. (i) Integrating the envelope condition $\pi'(\theta) = f(k(\theta))$ on $[\theta_l, \theta]$ we have $\pi(\theta) = \pi(\theta_l) + \int_{\theta_l}^{\theta} f(k(s))ds$. Substituting this expression for $\pi(\theta)$ in the objective function we obtain

$$\int_{\theta_l}^{\theta_h} (\theta f(k(\theta)) - rk(\theta) - \pi(\theta))\,dG = \int_{\theta_l}^{\theta_h} \left(\theta f(k(\theta)) - rk(\theta) - \int_{\theta_l}^{\theta} f(k(s))ds\right) dG - \pi(\theta_l).$$

where we have used $\int_{\theta_l}^{\theta_h} dG = 1$. We can transform the last term in the integral through the following integration by parts

$$-\int_{\theta_l}^{\theta_h} \left(\int_{\theta_l}^{\theta} f(k(s))\right) dG = \left[(1 - G(\theta))\int_{\theta_l}^{\theta} f(k(s))ds\right]_{\theta=\theta_l}^{\theta=\theta_h} - \int_{\theta_l}^{\theta_h} (1 - G(\theta))f(k(\theta))d\theta$$
$$= -\int_{\theta_l}^{\theta_h} (1 - G(\theta))f(k(\theta))d\theta$$

using $-dG = d(1-G)$ as the differentiated term in the integration by parts to obtain the first equality, and the fact that the bracketed term is zero since $G(\theta_h) = 1$ and $\int_{\theta_l}^{\theta_l} f(k(s))ds = 0$ for the second equality. Substituting this term in the objective function, the optimal choice of $(k(\theta), \pi(\theta_l))$ solves

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

Since the objective is strictly decreasing in $\pi(\theta_l)$ it is optimal to set the rent of the lowest type to zero, thus $\pi(\theta_l) = 0$. Pointwise maximization with respect to size yields the optimal $k_{mp}(\theta)$. Types such that $\theta < H(\theta)$ are excluded. The monotone hazard rate condition ensures that $\theta - H(\theta)$ is strictly increasing and thus, if there exists a type for which $\theta - H(\theta) = 0$ it is unique and types to the left of it are excluded. For types that are not excluded it is optimal to set the pointwise derivative equal to zero, yielding $(\theta - H(\theta))f'(k_{mp}(\theta)) = r$. Note that the Inada conditions imply that this equation admits a unique solution for each θ that is not excluded so the function $k_{mp}(\theta)$ is well defined. Also, differentiating the first order condition for types that are not excluded we obtain $k'_{mp} = -(1 - H')f'/(\theta - H)f''$ and thus the monotone hazard rate condition $H' \leq 0$ ensures that $k_{mp}(\theta)$ is strictly increasing.

[72] See Myerson (1979, 1981).

[73] As we have noted above, the Mafia can always choose for some type the zero level of size and transfers, which amounts to that type effectively not opening for business, so that imposing that each type "participates" is without loss of generality.

(ii) The rent function at the optimal solution is found by integrating, $\pi_{mp}(\theta) = \int_{\theta_l}^{\theta} f(k_{mp}(s))ds$. The optimal transfer function is then the difference between gross profits and the rent, $x_{mp}(\theta) = \theta f(k_{mp}(\theta)) - rk_{mp}(\theta) - \pi_{mp}(\theta)$.
(iii) For types that are not excluded $k_{mp}(\theta)$ is strictly increasing, so the inverse $\theta_{mp}(k)$ exists and it is strictly increasing. Define pizzo as a function of the observable level of capital as $x_*(k) = x_{mp}(\theta_{mp}(k))$, and note that the domain of the function is the interval $[k_l, k_h]$ where $k_i, i = l, h$ are defined as $k_i = k_{mp}(\theta_i)$. Taking derivatives we obtain

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

A firm of type θ that faces the pizzo function $x_*(k)$ chooses k to maximize $\theta f(k) - rk - x_*(k)$. The first derivative of this expression is zero at the level of k for which $\theta = \theta_{mp}(k)$. This means that the level of capital chosen by type θ is the one assigned to that type by the optimal direct mechanism, and therefore the function $x_*(k)$ implements that mechanism. Moreover, by the first order condition of the Mafia we have $\theta_{mp}(k)f'(k) - r = H(\theta_{mp}(k))f'(k)$. Since $f'' < 0$, $H' < 0$ and $\theta'_{mp}(k) > 0$ we conclude that $x''_*(k) < 0$ so the extortion function is strictly concave.

Last, we wish to prove that the fraction of gross profits appropriated by the Mafia $x_*(k)/(\theta_{mp}(k)f(k) - rk)$ is strictly decreasing in size. Since $x_*(k) = \theta_{mp}(k)f(k) - rk - \pi_{mp}(\theta_{mp}(k))$ we need to show that the ratio $\pi_{mp}(\theta_{mp}(k))/(\theta_{mp}(k)f(k) - rk)$ is increasing on the open interval (k_l, k_h). We will apply the following "de L'Hopital" kind of rule to this ratio:

Lemma 3 (Anderson et al., 2006, Pinelis, 2001). *Let $n(x), d(x)$ be differentiable functions and let $d'(x)$ never vanish on an open interval (a, b) in $\mathbb{R}$.*

If (l. (i) $dd' > 0$ on (a,b), (l.ii) $\limsup_{x\to a} d(x)^2(n/d)'(x)/|d'(x)| \geq 0$ and (l.iii) $n'(x)/d'(x)$ is increasing on (a,b), then $(n/d)' > 0$ on (a, b)

Our assumptions allow applying the Implicit Function Theorem to the first order condition to deduce that the function $k_{mp}(\theta)$ and its inverse are differentiable, and they allow applying the Fundamental Theorem of Calculus to the function $\pi_{mp}(\theta_{mp}(k)) = \int_{\theta_l}^{\theta_{mp}(k)} f(k_{mp}(s))ds$ to conclude it is also differentiable. For ease of notation, below we define $\pi_{mp}(\theta_{mp}(k)) = \pi(k)$. We need to prove (l.i)-(l.iii).

(l.i) The denominator of the ratio $\theta_{mp}(k)f(k) - rk$ is equilibrium gross profits for a firm that chooses k. Net profits π are strictly positive on (k_l, k_h) since $\pi(k_l) = 0$ and $\pi' > 0$, therefore gross profits are strictly positive as well. The denominator is also strictly increasing on (k_l, k_h) as $\theta'_{mp}(k)f(k) + \theta_{mp}(k)f'(k) - r = \theta'_{mp}(k) + Hf' > 0$ because $\theta'_{mp}(k) > 0$ by the monotone hazard rate property, and $Hf' > 0$ since by assumption f is strictly increasing and by definition $H(\theta_{mp}(k))$ is strictly positive on (k_l, k_h).

(l.ii)

$$\limsup_{k\to k_l} \frac{(\theta_{mp}(k)f(k) - rk)^2}{|(\theta_{mp}(k)f(k) - rk)'|}\left(\frac{\pi(k)}{\theta_{mp}(k)f(k) - rk}\right)' =$$
$$= \limsup_{k\to k_l} \pi'(k)\frac{\theta_{mp}(k)f(k) - rk}{|(\theta_{mp}(k)f(k) - rk)'|} - \pi(k)\frac{(\theta_{mp}(k)f(k) - rk)'}{|(\theta_{mp}(k)f(k) - rk)'|}$$
$$= \limsup_{k\to k_l} \pi'(k)\frac{\theta_{mp}(k)f(k) - rk}{|(\theta_{mp}(k)f(k) - rk)'|} \geq 0$$

The last line follows from $\pi(k_l) = 0$, $\pi'(k) = \theta'_{mp}(k)f(k) > 0$ and $\theta_{mp}(k)f(k) - rk > 0$.

(l.iii) We need to show that the ratio

$$\frac{\pi'(k)}{(\theta_{mp}(k)f(k) - rk)'} = \frac{\theta'_{mp}(k)f(k)}{\theta'_{mp}(k)f(k) + \theta_{mp}(k)f'(k) - r} = \frac{1}{1 + \frac{H(\theta_{mp}(k))f'(k)}{\theta'_{mp}(k)f(k)}}$$

is increasing, for which it suffices that the ratio

$$\frac{H(\theta_{mp}(k))f'(k)}{\theta'_{mp}(k)f(k)}$$

is decreasing. All its terms are positive and the numerator is decreasing by monotone hazard rate and concavity of f, thus it suffices that the denominator is increasing. The function $\theta_{mp}(k)$ can be defined from the first order condition in (i). Letting $\Gamma = (\theta - H(\theta))^{-1}$, which exists and it is strictly increasing since $\theta - H(\theta)$ is strictly increasing, we have $\theta_{mp}(k) = \Gamma\left(\frac{r}{f'(k)}\right)$. Taking the derivative we have $\theta'_{mp}(k) = -r\Gamma'(\cdot)\frac{f''(k)}{f'^2}$, thus the denominator of the ratio is $\theta'_{mp}(k)f(k) = r\Gamma'\left(\frac{r}{f'(k)}\right)\frac{|f''|/f'}{f'/f}$. Since the function f is homogeneous of degree α, by Euler's theorem we have $\alpha f(k) = kf'(k)$ and $(\alpha - 1)f'(k) = kf''(k)$, therefore the ratio $\frac{|f''|/f'}{f'/f}$ is a positive constant. By concavity of f the function $r/f'(k)$ is increasing, thus for $\theta'_{mp}(k)f(k)$ to be increasing it suffices that Γ be convex. Now Γ is the inverse of a strictly increasing function, and thus it is convex if $\theta - H(\theta)$ is concave, which is the case since we assume $H(\theta)$ convex. Applying Lemma 3 we conclude that $\pi_{mp}(\theta_{mp}(k))/(\theta_{mp}(k)f(k) - rk)$ is increasing, and thus the fraction of profits appropriated by the Mafia is decreasing in size. ■

Our empirical specification is based on applying a function of the form $x(k) = Bk^\alpha$ to the data. 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 on each type, that is $k_{fb}(\theta) = (\alpha\theta/r)^{1/(1-\alpha)}$ 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.

Appendix D. A weak Mafia

In this section we consider the problem of a Mafia which is constrained in the amount of damage that it can inflict on the firm if it refuses to pay. We keep all the notation and assumptions of the model in the main text, except that here the monetary equivalent z of the damage inflicted as punishment for not paying is equal to a fraction αk of firms' size, up to a maximum level Z, with $0 < \alpha < 1$ and $Z > 0$. Thus, the firm that enters anticipating not paying would choose k to solve $\max_{k\geq 0}\{\theta f(k) - rk - \min\{\alpha k, Z\}\}$. Denoting with $s_c^{fb}(\theta) = \max_{k\geq 0}\{\theta f(k) - ck\}$ the efficient level of surplus for a firm with cost c, and with k_c^{fb} the related choice of size, if the firm enters the market the best alternative to paying extortion for a type θ is $o(\theta) = \max\{s_{r+\alpha}^{fb}(\theta), s_r^{fb}(\theta) - Z\}$, which we assume to be larger than the profits from not opening at all. It is of course in the interest of the Mafia that firms entering the market pay the extortion, thus we impose $\pi(\theta) \geq o(\theta)$. To make the problem interesting we assume that there exists $\hat{\theta} \in (\theta_l, \theta_h)$ such that $s_{r+\alpha}^{fb}(\hat{\theta}) = s_r^{fb}(\hat{\theta}) - Z$. Since $s_r^{fb}(\theta)$ is steeper than $s_{r+\alpha}^{fb}(\theta)$ we have that for $\theta < \hat{\theta}$ the relevant outside option is $s_{r+\alpha}^{fb}(\theta)$ and for $\theta \geq \hat{\theta}$ it is $s_r^{fb}(\theta) - Z$. The maximization problem of a weak Mafia becomes

$$\begin{aligned} &\max_{k(\theta),\pi(\theta)} \int_{\theta_l}^{\theta_h} (\theta f(k(\theta)) - rk(\theta) - \pi(\theta))dG \\ &s.t. \quad \pi'(\theta) = f(k(\theta)) \\ &\qquad \pi(\theta) \geq s_{r+\alpha}^{fb}(\theta) \text{ if } \theta \leq \hat{\theta} \\ &\qquad \pi(\theta) \geq s_r^{fb}(\theta) - Z \text{ if } \theta \geq \hat{\theta} \\ &\qquad k'(\theta) \geq 0 \end{aligned} \tag{wm}$$

To solve the problem we resort to Jullien (2000, Th.1). There exists a cumulative multiplier $\gamma_{wm}(\theta)$ on the set of types such that the optimal solution $k_{wm}(\theta)$ is continuous, $\pi_{wm}(\theta)$ absolutely continuous and satisfies the following conditions:

$$(\theta - \frac{\gamma_{wm}(\theta) - G(\theta)}{g(\theta)})f'(k_{wm}(\theta)) = r \tag{4}$$

$$\int_{\theta_l}^{\theta_h} (\pi(\theta) - o(\theta))d\gamma_{wm}(\theta) = 0 \tag{5}$$

In order to characterize the solution, note that whenever the participation constraint is binding for $\theta \leq \hat{\theta}$ it must be $k_{wm} = k_{r+\alpha}^{fb}$, and for $\theta \geq \hat{\theta}$ it must be $k_{wm} = k_r^{fb}$. Moreover, whenever the participation constraint is not binding $\pi > o$ it must be that $d\gamma_{wm} = 0$, so that γ_{wm} is constant.

The solution is such that there are (possibly empty) intervals of types at the bottom interval $[\theta_l, \theta_a]$ and at top interval $[\theta_b, \theta_h]$, $\theta_a \leq \hat{\theta} \leq \theta_b$, where the participation constraint is binding, while it is slack for $\theta_a < \theta < \theta_b$. The following choice for the multiplier:

$$\gamma_{wm}(\theta) = \begin{cases} G(\theta) + \frac{\alpha}{r+\alpha}\theta g(\theta) & \text{if } \theta_l \leq \theta \leq \theta_a \\ \hat{\gamma} & \text{if } \theta_a \leq \theta \leq \theta_b \\ G(\theta) & \text{if } \theta_b \leq \theta \leq \theta_h \end{cases}$$

with a constant $\hat{\gamma}$ gives the proposed solution as long as the resulting $(k_{wm}(\theta), \pi_{wm}(\theta)$ are both continuous. Imposing continuity will give two equations that solved together yield the pair θ_a, θ_b, if interior to the type space.[74] First, we set $\hat{\gamma} = G(\theta_b)$ so that k_{wm} is continuous at θ_b and we impose the condition

$$\frac{G(\theta_b) - G(\theta_a)}{\theta_a g(\theta_a)} = \frac{\alpha}{r+\alpha}. \tag{6}$$

[74] Depending on the parameters, it is of course possible that one or both intervals where participation should be binding are empty.

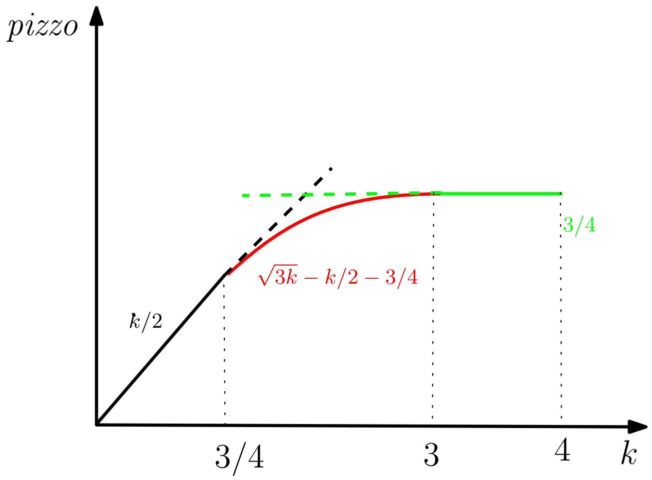


Fig. 15. The *pizzo* function for a weak mafia.

which makes it also continuous at θ_a. Second, we require that π meets o at θ_a and θ_b. Denote with $\hat{k}(\theta, G(\theta_b))$ the solution of Eq. (4) when $\gamma_{wm} = \hat{\gamma} = G(\theta_b)$. Integrating the incentive compatibility condition on $[\theta_a, \theta_b]$ we can write $\pi(\theta_b) = \pi(\theta_a) + \int_{\theta_a}^{\theta_b} f(\hat{k}(\theta, G(\theta_b)))d\theta$. Substituting π with o at θ_a and θ_b we obtain

$$s_r^{fb}(\theta_b) - Z = s_{r+\alpha}^{fb}(\theta_a) + \int_{\theta_a}^{\theta_b} f(\hat{k}(\theta, G(\theta_b)))d\theta \tag{7}$$

The optimal level of size is therefore given by:

$$k_{wm}(\theta) = \begin{cases} k_{r+\alpha}^{fb}(\theta) & \text{if } \theta_l \leq \theta \leq \theta_a \\ \hat{k}(\theta, G(\theta_b)) & \text{if } \theta_a \leq \theta \leq \theta_b \\ k_r^{fb}(\theta) & \text{if } \theta_b \leq \theta \leq \theta_h \end{cases} \tag{8}$$

where θ_a, θ_b are given by the solution to Eqs. (6)–(7), provided they are interior to the type space. Denoting with $\hat{\theta}_{wm}(k, G(\theta_b))$ the inverse of $\hat{k}(\theta, G(\theta_b))$, which exists because of the monotone hazard rate property, the corresponding *pizzo* function solution to the weak mafia problem is:

$$x_{wm}^{\star}(k) = \begin{cases} \alpha k & \text{if } k_{r+\alpha}^{fb}(\theta_l) \leq k \leq k_{r+\alpha}^{fb}(\theta_a) \\ \begin{bmatrix} \hat{\theta}_{wm}(k, G(\theta_b)) f(k) - rk - s_{r+\alpha}^{fb}(\theta_a) \\ -\int_{\theta_a}^{\hat{\theta}_{wm}(k, G(\theta_b))} f(\hat{k}(\theta, G(\theta_b)))d\theta \end{bmatrix} & \text{if } k_{r+\alpha}^{fb}(\theta_a) \leq k \leq k_r^{fb}(\theta_b) \\ Z & \text{if } k_r^{fb}(\theta_b) \leq k \leq k_r^{fb}(\theta_h) \end{cases}$$

This function implements Eq. (8). Before commenting on the solution we provide a simple parametric example for which Eqs. (6)–(7) can be solved analytically. Let $f(k) = 2\sqrt{k}$ and θ distributed uniformly on $[1, 2]$. The solution to Eqs. (6)–(7) is:

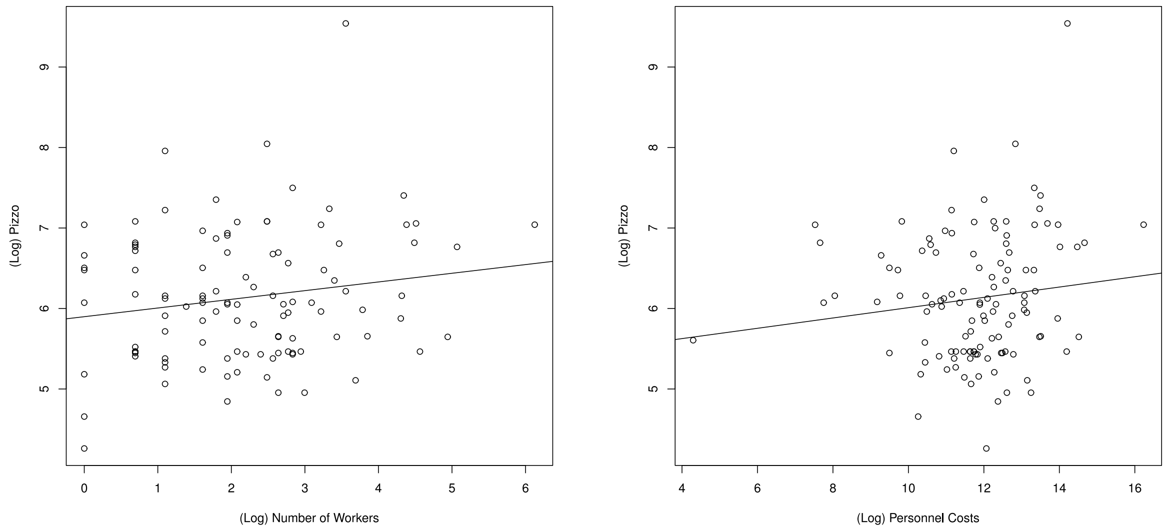
$$\theta_a = \sqrt{\frac{Zr(r+\alpha)^2}{\alpha(r+2\alpha)}}, \quad \theta_b = \sqrt{\frac{(r+2\alpha)rZ}{\alpha}}$$

which is interior if $Z \in [\frac{\alpha(r+2\alpha)}{r(r+\alpha)^2}, \frac{4\alpha}{(r+2\alpha)r}]$. The pizzo function in this example is:

$$x_{wm}^{\star}(k) = \begin{cases} \alpha k & \text{if } (\frac{1}{r+\alpha})^2 \leq k \leq \frac{Zr}{\alpha(r+2\alpha)} \\ \sqrt{\frac{(r+2\alpha)rZ}{\alpha}k} - \frac{kr}{2} - \frac{rZ}{2\alpha} & \text{if } \frac{Zr}{\alpha(r+2\alpha)} \leq k \leq \frac{Z(r+2\alpha)}{r\alpha} \\ Z & \text{if } \frac{Z(r+2\alpha)}{r\alpha} \leq k \leq \frac{4}{r^2} \end{cases}$$

In Fig. 15 we represent the function for $\alpha = 1/2$, $r = 1$, $Z = 3/4$. In the black and green regions participation is binding, in the red region it is not. In this extension of the model the pizzo function is still concave. Since the participation constraint binds for intervals at the extrema of the size distribution, there the pizzo function agrees with the level of punishment. That is, the Mafia demands just enough to make firms comply with its requests.

More specifically, for small firms the Mafia is able to inflict a punishment that is proportional to k, thus the pizzo increases linearly with size. For large firms the maximum punishment level is reached and the Mafia can do no better than ask for this flat fee. This in turn implies that the choice of size for large firms is at first best. Indeed, the choice of size is everywhere closer to



(a) *Pizzo* and Number of Employees (b) *Pizzo* and Personnel Costs

Fig. 16. The relation between *pizzo* and employment-related measures of size.

efficiency than in the case of a strong Mafia. At the bottom, a strong Mafia would charge a marginal pizzo larger than α, thus inducing a larger distortion which would violate the participation constraint. For medium-sized firms the marginal pizzo depends on the familiar trade-off between efficiency and rent extraction. However, a weak mafia takes into account that there is a non-empty set of types, the ones that pay the flat fee Z, whose rent is unaffected by the marginal pizzo paid by lower types, and thus finds less reason to distort these medium-sized types with a larger marginal pizzo.[75]

Appendix E. Robustness checks

In this Appendix we report various robustness checks using different measures of size and extending the sample to partnerships. All extensions that we present are consistent with the main results of our preferred sample and model specification in the main text.

E.1. Scatterplots

Fig. 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 it may appear in the documents accompanying the financial statements. For every company, we extracted all the available information on this number and calculated the average across the period we are studying, although in the vast majority of cases we have only one data per firm.

E.2. Regressions

Table 9 contains the results of the models estimated in Table 2 excluding the highest level of *pizzo*. Table 10 contains the estimation of the models of Table 2 which consider firm revenues as a measure of size, while Table 11 contains the estimation of the same models excluding the highest *pizzo* value.

Table 12 shows the results of estimating Eq. (3) when revenue is the measure of firm size.

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

Table 14 contains the results of estimates of the elasticities of firm taxes with respect to firm revenues.

Tables 15 and 16 contain the results of regressions, respectively, with personnel costs and number of employees as the measure of firm size using our original sample of limited liability companies.

Table 17 contains the results of regressions of the *pizzo* rate on total fixed assets when any firm for which either the pizzo is larger than profits or the profits are negative is assigned a value of 1 to its *pizzo* rate.

Table 18 contains the results of regressions of the *pizzo* rate on firm's total fixed assets when the *pizzo* rate is computed on after-tax profits.

[75] This can be seen formally comparing Eq. (4) to (i) in Proposition 1 and noting that $G(\theta_b) < 1$ if the set of types whose participation constraint binds at the top is non-empty.

Table 9
Pizzo and 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***
	(0.585)	(0.399)	(0.561)	(0.671)	(0.508)	(0.711)
Total Fixed Assets (log)	0.035	0.068**	0.059**	0.042	0.133***	0.105***
	(0.026)	(0.027)	(0.024)	(0.036)	(0.037)	(0.034)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 10
Pizzo and 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***
	(1.114)	(0.985)	(1.118)	(1.140)	(0.981)	(1.039)
Revenues (log)	0.035	0.145**	0.091*	−0.013	0.179***	0.129***
	(0.044)	(0.060)	(0.047)	(0.064)	(0.058)	(0.045)
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	0.232	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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 11
Pizzo and 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***
	(0.725)	(0.666)	(0.755)	(1.150)	(0.986)	(1.022)
Revenues (log)	−0.001	0.090**	0.047	−0.020	0.164***	0.113**
	(0.034)	(0.039)	(0.033)	(0.064)	(0.058)	(0.044)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 12
Pizzo and 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***
	(0.956)	(0.933)	(1.068)	(1.123)	(0.947)	(1.193)
Revenues (log)	0.035	0.043	−0.015	−0.008	0.070	0.031
	(0.041)	(0.058)	(0.053)	(0.065)	(0.057)	(0.057)
Revenues (log) x D	0.045***	0.207*	0.215**	0.022	0.331***	0.313**
	(0.014)	(0.119)	(0.106)	(0.017)	(0.122)	(0.121)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 13
Pizzo rate and Revenues (OLS and WLS).

	Dependent variable:					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	6.745***	7.720***	7.283***	6.810***	7.623***	6.812***
	(1.292)	(2.016)	(1.689)	(1.641)	(2.436)	(2.146)
Revenues (log)	−0.809***	−0.720***	−0.808***	−0.888***	−0.720***	−0.814***
	(0.076)	(0.121)	(0.083)	(0.088)	(0.146)	(0.108)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	No	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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Finally, Table 19 contains the results when the pizzo rate is assigned a value of 1 for firms with negative after-tax profits and pizzo rate (on after-tax profits) > 1.

E.3. Pizzo and number of employees in the extended sample

In this appendix we present the results based on a larger sample, including both the limited liability companies and the partnerships, with the number of employees as the common measure of firm size.

Let us provide some descriptive evidence of this larger sample. First of all, the distribution of *pizzo* values across the two types of firms is different. The means and standard deviations are, respectively for limited liability firms and partnerships, €689 (s.d.: 1312) and €363 (s.d.: 475). That is, the distribution for limited liability firms has a higher mean and is more dispersed.

In both cases, the most represented sectors are: Construction, Motor Vehicles Repair, Wholesale trade, Retail trade, Hotels and Restaurants, Land Transport, with a share of observations from these sectors, respectively for limited liability companies and partnerships, of 73% and 86%. Retail trade is particularly represented in the partnerships, with 74 observations (39%).

In terms of number of employees, partnerships are on average much smaller than the limited liability firms. In fact, the average numbers of employees for the two types of companies are, respectively, 4.39 (s.d. 5.9) and 21.76 (s.d. 49.95). A relatively high number of partnerships ()58) declared to have only one employee.

Fig. 17 shows the bivariate relation between (log) *pizzo* and (log) number of employees for the full sample with limited liability firms and partnerships, highlighting that it still has a moderately upward-sloping shape (the estimated coefficient of the bivariate relation is 0.16, significant at 1‰).

Table 14
Taxes and 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***
	(1.249)	(1.457)	(1.622)	(1.014)	(1.962)	(2.059)
Revenues (log)	0.904***	0.908***	0.952***	0.928***	1.046***	0.988***
	(0.072)	(0.091)	(0.092)	(0.058)	(0.124)	(0.113)
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: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 15
Pizzo and Personnel Costs (OLS and WLS).

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.373***	4.009***	5.109***	5.382***	3.504***	4.968***
	(0.853)	(0.579)	(0.844)	(0.620)	(0.392)	(0.701)
Personnel Costs (log)	0.026	0.099**	0.050	0.030	0.142***	0.106**
	(0.039)	(0.046)	(0.039)	(0.037)	(0.029)	(0.041)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	No	No	Yes	Yes
Observations	116	116	116	116	116	116
Adjusted R^2	0.247	0.170	0.297	0.428	0.547	0.630
Residual Std. Error	0.690	0.724	0.667	3.614	3.218	2.908
F Statistic	2.714***	1.786**	2.080***	4.914***	5.622***	5.347***

Note: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 16
Pizzo and Number of Employees (OLS and WLS).

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.553***	4.789***	5.588***	5.614***	4.807***	6.320***
	(0.647)	(0.291)	(0.669)	(0.452)	(0.314)	(0.704)
Number of Employees (log)	0.054	0.138**	0.050	0.054	0.130*	0.006
	(0.056)	(0.063)	(0.056)	(0.066)	(0.068)	(0.066)
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	109	109	109	109	109	109
Adjusted R^2	0.225	0.164	0.253	0.406	0.516	0.598
Residual Std. Error	0.712	0.740	0.699	3.732	3.368	3.071
F Statistic	2.424***	1.704**	1.811**	4.353***	4.839***	4.564***

Note: robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 17
Pizzo rate and Total Fixed Assets (OLS and WLS). *Pizzo* rate = 1 for firms with negative profits and for those with *pizzo* rate > 1.

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.093	0.184	−1.502	0.009	−0.930	−2.236
	(0.995)	(1.217)	(1.711)	(1.419)	(1.454)	(2.287)
Total fixed assets (log)	−0.361***	−0.357***	−0.349***	−0.398***	−0.273***	−0.317***
	(0.062)	(0.069)	(0.069)	(0.082)	(0.088)	(0.084)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	No	No	Yes	Yes
Observations	119	119	119	119	119	119
Adjusted R^2	0.252	0.284	0.237	0.433	0.632	0.616
Residual Std. Error	1.426	1.395	1.440	8.339	6.720	6.863
F Statistic	2.812***	2.563***	1.816**	5.089***	7.742***	5.201***

Note: Robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 18
Pizzo rate (on after-tax profits) and Total Fixed Assets (OLS and WLS).

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.222*	2.477*	1.823	3.401*	3.754**	4.426***
	(1.148)	(1.266)	(1.551)	(1.871)	(1.434)	(1.579)
Total Fixed Assets (log)	−0.505***	−0.480***	−0.477***	−0.576***	−0.596***	−0.595***
	(0.076)	(0.089)	(0.089)	(0.122)	(0.097)	(0.081)
Time Dummies	Yes	No	Yes	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	No	No	Yes	Yes
Observations	90	90	90	90	90	90
Adjusted R^2	0.294	0.491	0.445	0.628	0.923	0.932
Residual Std. Error	1.547	1.313	1.371	10.360	4.708	4.438
F Statistic	2.683***	3.956***	2.620***	7.844***	37.925***	28.642***

Note: Robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 19
Pizzo rate (on after-tax profits) and Total Fixed Assets (OLS and WLS). *Pizzo* rate = 1 for firms with negative profits and for those with *pizzo* rate > 1.

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.750	−0.072	−2.203	3.401*	−1.184	−2.802
	(0.929)	(1.147)	(1.602)	(1.871)	(1.342)	(2.106)
Pizzo Rate (log)	−0.321***	−0.334***	−0.310***	−0.576***	−0.253***	−0.279***
	(0.059)	(0.066)	(0.064)	(0.122)	(0.080)	(0.079)
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	0.273	0.306	0.285	0.298	0.632	0.615
Residual Std. Error	1.328	1.298	1.318	8.369	6.057	6.196
F Statistic	3.019***	2.733***	2.046***	3.274***	7.759***	5.191***

Note: Robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

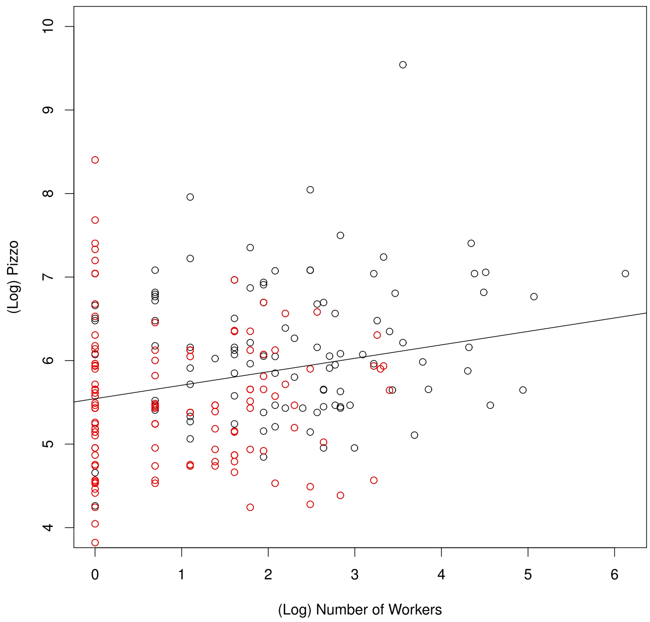


Fig. 17. *Pizzo* and number of employees: Limited Liability (black) and Partnerships (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 20
Pizzo and Number of Employees (OLS and WLS).

	Dependent variable:					
	log (pizzo)					
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	7.222***	6.267***	6.060***	7.646***	6.501***	6.360***
	(0.182)	(0.213)	(0.308)	(0.300)	(0.187)	(0.331)
Number of Employees (log)	0.139***	0.156***	0.137***	0.085	0.145**	0.140***
	(0.044)	(0.042)	(0.041)	(0.071)	(0.062)	(0.040)
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	240	240	240	240	240	240
Adjusted R^2	0.265	0.310	0.356	0.414	0.601	0.750
Residual Std. Error	0.737	0.714	0.690	4.745	3.919	3.099
F Statistic	4.446***	3.906***	3.443***	7.765***	10.711***	14.295***

Note: Robust standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01.

Table 20 reports the results of the econometric analysis of the relationship, along the lines of the estimations presented in the main text with total fixed assets as a measure of size.[76]

Results of Table 20 are consistent with those in the main text, both in terms of the magnitude of the estimated coefficients and of their significance.

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[76] Weights for partnerships in the WLS estimations are computed in the same way as the weights for the limited liability companies (see Footnote 42 for details), considering the population of partnerships in Sicily.

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