Mafia and Misallocation in Northern Italy:

a new approach of estimating the cost of organised crime *

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Abstract

This paper studies how the response of firms to mafia infiltrations can generate economic costs. I argue both theoretically and empirically that acts of extortion imposed to firms located in Northern Italy are linked to resource misallocation, which is measured using the within-industry covariance between size and productivity. I develop a novel methodology to quantify the share of output that mafia groups extort from firms. This transfer ranges between 1 and 8 percent of firm-level output for the taxed firms. I also simulate the counterfactual northern Italian economy without infiltrations and estimate the cost due to mafia expansion. The results suggest that the northern Italian economy, between 2000 and 2012, suffered an aggregate loss of approximately 2.5 billion Euros. Only one fourth of this cost is the aggregate transfer to mafia groups. The remaining three fourths correspond to the contraction of production due to misallocation.

Keywords: Extortion, Misallocation, Welfare Loss, Organised Crime, Italian Mafia, OP covariance

JEL Codes: C5 O4 D21 D22 D73

1 Introduction

Organised crime is a frightening phenomenon present in almost every country in the world. Criminal organisations engage in a wide range of economic activities, both legal and illegal, and generate huge revenues. For example, the UN Office of Drugs and Crime (2012) has reported that the annual turnover of transnational organised criminal activities is comparable to 1.5% of the global GDP. Measuring the economic consequences of organised crime is thus a relevant question as well as challenging task, because of the hidden nature of this phenomenon.

This paper develops a method to estimate the cost of organised crime, which uses panel data in a structural model that builds on the large literature on misallocation among heterogeneous producers (see, for example, Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Bartelsman et al. (2013)). I focus on the Italian mafia, one of the most famous criminal organisations in the world, and I study its impact on the northern Italian economy. In particular, I analyse firms' response to extortion, a central mafia activity that has been classified as one of its largest sources of profit.[1] By successfully forcing entrepreneurs to pay *pizzo* (the world *pizzo*, derived from the Sicilian language, indicates the extortion perpetrated by the mafia), mafia groups guarantee themselves control over the infiltrated territories and a stable flow of income (Konrad and Skaperdas, 1998). Supposedly, what is a gain for the mafia is a cost for the economy. In addition to the output losses from extortion, there is a cost in terms of reduction in production, which can be seen as a welfare loss. The method I develop in this study provides a way to estimate the amount of *pizzo* imposed in northern Italy, and a way to think about the welfare

[1] The spread of the mafia in northern Italy in the last decade has received considerable attention in the Italian news. A relatively recent investigation promoted by the Italian Ministry of the Interior (Transcrime, 2013) highlights a strong presence of mafia groups in the northern regions, especially in Piedmont, Lombardy and Emilia Romagna. Transcrime (2013) has estimated average revenues from mafia illegal activity. According to this report drug trafficking is the activity that generates the highest revenues (on average 7.7 billion euros), followed by extortion (4.7 billion euros), sexual exploitation (4.6 billion euros) and counterfeiting (4.5 billion euros).

loss that occurs by transferring resources to mafia groups that would otherwise have been used productively.

To examine the effects of extortion on the northern Italian economy, I propose a standard multi-sectorial model of heterogeneous producers. Specifically, firms differ in their productivity level and choose employment to produce in a monopolistic competition environment. *Pizzo* is a proportional tax on firm-level output, this distortion is idiosyncratic because notably some producers do not face mafia intervention, while others do. A central prediction of the model is that in an environment without the mafia, the distribution of firms' productivity and the distribution of their sizes, measured respectively with revenue per worker and firm-level employment, are perfectly correlated. Instead, if the mafia infiltrates the market and coerces a randomly chosen group of firms, the strength of the link between the two distributions is weakened, meaning that the market is affected by resource misallocation.

The key insight of this paper is the methodology I develop to obtain a quantitative estimate of the amount of *pizzo* imposed in the northern territories. This method implements tools both from panel data analysis and structural econometrics, and uses actual data on the distortion that creates misallocation, i.e. information on the number of firms that suffered extortion. As a first step, I define mafia and non-mafia infiltrated markets and I estimate the parameters of the model that are unrelated to the mafia in a environment with no distortions. I do this by imposing zero extortion and using the results of the theoretical model to estimate the parameters of interest using data from non-mafia environments. This means that, in a way, I use non-mafia markets as the best counterfactual for the infiltrated markets if the mafia were not coercing firms. Second, I feed the model with these parameters and with the observed difference of the share of extorted firms between mafia and non-mafia environments. Together with the aggregate data on the mafia-infiltrated markets, this allows me to back out the magnitude of the tax imposed on firms. As a result, this paper provides the first estimate of the sectorial amount of *pizzo* imposed by mafia groups to firms that operate in northern Italy, which ranges between 1 and 8 percent of the output level of impacted firms. These estimates imply a total cost of almost 2.5 billion euros, which I obtain by performing a counterfactual analysis. Almost three-fourths of this cost can be seen as a welfare loss, as this share is the forgone output of the firms that are forced to pay *pizzo*. The remaining share is the aggregate transfer to mafia groups.

In order to determine what constitutes a mafia-infiltrated market, I employ the three-dimensional variation of the panel data at my disposal (sector-province-year) to: define a subgroup of industries as mafia-appealing; distinguish between infiltrated and not infiltrated provinces; and determine the timing of mafia arrival. I define mafia-infiltrated markets as specific sectors of the economy that are mafia-appealing, located in mafia infiltrated provinces, after mafia arrival. Using this distinction, I provide suggestive evidence that mafia presence correlates negatively with allocative efficiency, measured with the within-sector covariance between size and productivity introduced by Olley and Pakes (1996) (OP covariance henceforth). As Bartelsman et al. (2013) argue both theoretically and empirically, the within-industry heterogeneity in terms of firms' productivity coexists with heterogeneity in terms of size, and the distributions of productivity and size tend to be correlated. In markets without distortions, more productive firms are larger than the less productive ones. However, the strength of this relationship is weakened if firms face idiosyncratic distortions that impact their scale of businesses. Hence, the OP covariance between size and productivity can be used as an instructive measure to assess resource misallocation between firms.

Next, I model the mechanism through which the strength of the link between firm-level productivity and size depends on mafia infiltrations. I show that in a given sector of the economy, located in a northern province without mafia infiltrations, the rankings of firm-level productivity and firm-level size are perfectly aligned, meaning that the most productive firm is also the largest one, the second most productive firm is the second largest one, and so forth. If, instead, the mafia infiltrates the market, the most productive firm might no longer be the largest one. This means that extortion distorts the allocative efficiency of the impacted markets.

I then estimate this model structurally in two stages. In the first stage, I focus on non-mafia environments to measure the parameters of the model that are unrelated to the mafia from the following fixed effects of a system of equations: (i) sector-province, (ii) province-time, (iii) sector-time, (iv) sector. In the second stage, I apply the Method of Simulated Moments (MSM henceforth) to estimate the magnitude of *pizzo* for each mafia-infiltrated market. Essentially, I compute this tax imposed by mafia groups in each infiltrated market by matching the simulated OP covariance delivered by the model to the corresponding OP covariance observed in the data. I then use these results to perform model simulations aimed at understanding where the loss due to mafia infiltrations originates. As I final step, I measure this cost with a counterfactual analysis through which I compute the total amount of *pizzo* transferred to mafia groups and the aggregate value added of the northern Italian economy in the absence of mafia infiltrations.

This paper contributes to the significant existing body of the literature on the economic consequences of weak institutions. Taking a macro approach, Acemoglu et al. (2001) and Hall and Jones (1999) show how differences in institutions and government policies can explain why per capita income differs considerably among countries. An emerging strand of this literature joins the macro and the micro aspects, using firm-level data to analyse cross-country differences in income and aggregate productivity. In this perspective, Ranasinghe (2017) explores the role of property rights and their link to acts of extortion. Ranasinghe and Restuccia (2018) quantify the effects of institutional differences in the degree of financial development and the rule of law on aggregate outcomes and economic development. Finally, Besley and Mueller (2018) study the consequences of predation and estimate the welfare loss due to the misallocation of labour across firms and within firms, when labour is moved from production to protection. Compatibly with this literature, I study how extortion perpetrated by mafia groups affect the aggregate productivity and the allocative efficiency of the infiltrated markets. The main contribution of this paper is to widen the range of methods that can be used to explore this field, by proposing a new methodology that combines panel data and structural econometrics tools.

There is a large related literature on the economic cost of crime, which has been thoroughly reviewed by Soares (2010). There are some contributions that focus on organised crime. For example, Besley et al. (2015) explicitly address the welfare cost of Somali piracy using data on shipping contracts in the dry bulk market. Pinotti (2015) studies the economic consequences of mafia expansion in two southern regions not historically plagued by the mafia, and compute the cost of mafia expansion in terms of GDP per capita. Likewise, my analysis provides an explicit estimate of the cost of mafia diffusion in an area that has not yet been explored, northern Italy.

This paper relates also to a number of theoretical and empirical contributions on misallocation. The relationship between firm-level idiosyncratic distortions and aggregate productivity has been theorised by Restuccia and Rogerson (2008) and developed by Hsieh and Klenow (2009), who provide an empirical analysis of resource misallocation to explain cross-country difference in productivity, measured with Total Factor Productivity (TFP). Bartelsman et al. (2013) take a step further and propose the within-industry covariance between firms' productivity and size as the most instructive index of resource misallocation. Along these lines, I study how acts of extortion imposed by mafia groups to heterogeneous firms generate resource misallocation. I analyse this relationship *directly*, in the sense that I analyse the role of a specific distortion that is idiosyncratic across heterogeneous establishments.[2]

Naturally, this analysis adds to the literature on the economic impact of the Italian mafia. Barone and Narciso (2015), Acconcia et al. (2014), and Galletta (2017) look at the impact of mafia presence on public transfer to firms and on public spending. Pinotti (2013) and Daniele and Geys (2015) look at the implications of mafia presence on politicians' characteristics established in the infiltrated areas. The diffusion of mafia groups in new areas has been given little attention so far. Buonanno and Pazzona (2014) study possible channels that favoured the spreading of Italian mafia to the northern Italian provinces.[3] Moreover, Piemontese (2013) and Scognamiglio (2018) show that the construction sector is a crucial environment for mafia migration.

The remainder of the paper proceeds as follows. Section 2 introduces the data, presents a description of the OP covariance and documents some preliminary evidence. Section 3 lays out the model of misallocation and welfare loss due to mafia. Section 4 covers the description of its estimation. Section 5 illustrates the results of the model estimation, the model simulations and the counterfactual analysis which measures the cost suffered by the infiltrated northern territories. Section 6 considers two alternative specifications of the model. Section 7 concludes the paper.

2 Data and motivating evidence

In this section, I describe the data and how I define a mafia-infiltrated market. I then introduce the proxy for allocative efficiency, i.e. the OP covariance. Finally, I look at the relationship between mafia infiltrations and OP covariance using a reduced

[2]For a comprehensive review of the literature on misallocation and a deeper understanding of the difference between the *direct* and the *indirect* approach to the topic, see Restuccia and Rogerson (2013).

[3]In particular, the authors study the interaction between *Confino law* and the influx of southern workers into northern regions. *Confino* is a peculiar Italian policy measure that imposed the compulsory displacement of people strongly suspected of being part of mafia-like organisations.

form strategy which makes use of the three-dimensional variation (sector-province-year) of the data. Results show suggestive evidence of a negative and statistically significant correlation between mafia presence and allocative efficiency.

Mafia-infiltrated markets

The first step of this analysis is the definition of mafia-infiltrated markets, which are specific sectors of the economy located in mafia infiltrated provinces and observed after mafia arrival. This definition requires three distinctions, the first one is at the sector level. I recognise sectorial mafia presence using data about firms that have been seized by the judicial system because they were found to be directly managed or linked to mafia groups. The dataset, provided by the National Agency for the Administration and Management of Real Estate and Firms Confiscated from Criminal Organisations (ANBSC), reports information on the location and the sector to which the confiscated firm belongs, as well as the year of the final verdict of confiscation.[4]

Figure 1 ranks seven sectors of the economy according to the absolute and relative number (amount per 1000 firms) of firms seized from the mafia. Mafia industries are those with a high number of confiscations, while non-mafia industries have an absolute and relative number of confiscations that is close to zero. Following this criteria, mafia-appealing sectors are: accommodation and food service activities, construction, wholesale and retail trade, services, community social and personal services.[5]

The second and third dimensions needed to define infiltrated markets are province

[4] I can distinguish among seven 1-digit ISIC rev. 4 sectors. The five 2-digit ISIC rev. 4 manufacturing sub-sectors are grouped in one. I use this information only to distinguish among mafia-appealing sectors and the remaining ones. I don't exploit the time variation because the year of seizure could provide only a "vintage" measure of mafia presence, as years can pass between the initial mafia infiltration and the year of the final verdict of seizure.

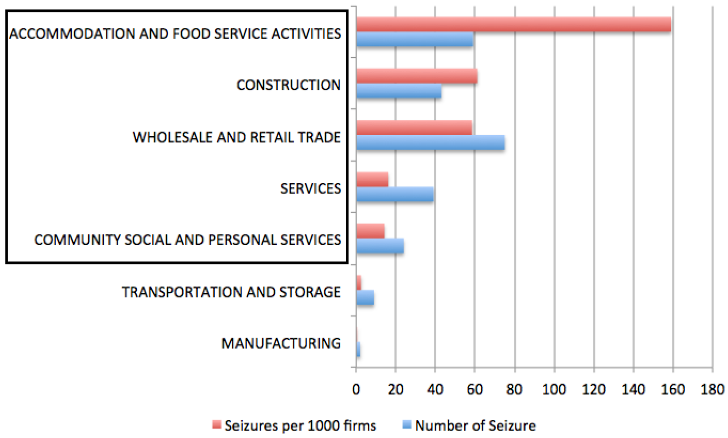
[5] Recall that, in my dataset, manufacturing is divided in six sub-sectors; thus the non-mafia appealing sectors are seven: the six manufacturing sub-sectors and transportation and storage sector.

and time. To define mafia-infiltrated territories and periods, I follow Piemontese (2013), which explores the role of public investment in infrastructure on mafia expansion in Northern Italy, and shows that there was a significant increase in extortion cases in the provinces that received funding for the modernisation of the A4 motorway and the construction of the high-speed rail between Milan and Bologna, after their approval between 2000 and 2002. According this paper, mafia infiltrated provinces are those that received public funding for the renewal of the Turin-Trieste highway and/or the Milan-Bologna railway. These provinces are visible in Figure 2, which maps the northern territories and the infrastructure studied by Piemontese (2013). For each infiltrated province, the mafia period starts with the approval of the funding, hence in year 2000 for some provinces and in year 2002 for the remaining provinces. Given the little available work on mafia diffusion in northern Italy, there is not a unique theory on when exactly mafia groups migrated towards the northern regions. Other studies assume that the mafia started moving in the late 70s, both because of legal practices forcing suspected *mafiosi* (people linked to the mafia) to relocate to towns that were historically unaffected by the mafia and due to migration flows from southern Italy (Buonanno and Pazzona (2014) and Scognamiglio (2018)).[6] The assumption of these studies of an earlier arrival does not necessarily contradict the assumption used in this paper, of a later arrival. Even if *mafiosi* might have reached the north before the 2000s, it is plausible to assume a time lag between the mere arrival and the effective infiltration of the legal economy, which boomed in the early 2000s.

To sum up, the definition of a mafia-infiltrated market employed in this study relies on the simultaneous occurrence of industrial, geographical, and temporal dimensions: the sectors of the economy defined as mafia appealing (Figure 1), located in the mafia provinces (Figure 2), and observed after year 2000 or 2002.

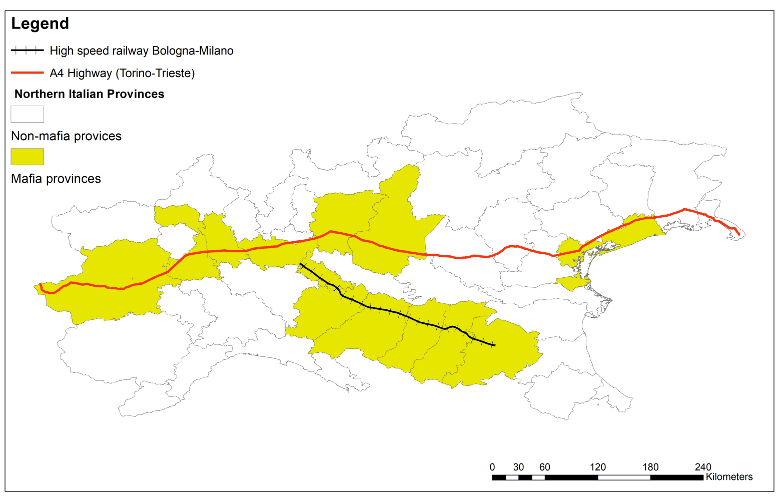
[6]Both Buonanno and Pazzona (2014) and Scognamiglio (2018) focus on northern and central regions, thus their results do not specifically refer to the regions where I base my analysis.

Figure 1: Sectorial Mafia Presence



Source: Computations based on ANBSC on seized firms from the mafia.

Figure 2: Provincial Mafia Presence



Source: Computations based on ISTAT yearly book of criminal statistics (ed. 2014).

Data

The three-dimensional panel dataset employed in this analysis uses data from the *Survey on Small and Medium Enterprises* provided by the Italian National Statistical Institute (ISTAT). This dataset collects information on small and medium enterprises (SME) registered in the Italian Statistical Firms Register (ASIA). The data is stratified by sector, year, and geographical region and is representative of the universe of the SMEs operating in Italy. I use a subsample that includes information on firms operating in the northern regions over the time period from 1998 to 2012. The resulting dataset, containing between 20,000 and 29,000 observations per year, provides information on location, sector, employment, sales and expenditure in intermediate inputs.[7] Data on sales and inputs is deflated with an industry-level deflator.[8] I aggregate this firm-level data at sector-province-year level.[9] The resulting dataset is an unbalanced panel dataset that provides information on the 46 northern Italian provinces, over 12 sectors, from 1998 to 2012.[10] The variables included in the dataset are: OP covariance (in terms of value added per worker and share of employment over total industry employment), mean and variance of labour, mean and variance of value added, mean and variance of value added per worker (all the variables are both in levels and logs).

I measure mafia intensity using information on reports of extortion provided by the Yearly Book of Criminal Statistics published by the Italian Statistical Institute (ISTAT). Figure 3 shows the average extortion cases over time for two groups of observations: mafia and non-mafia provinces. Average extortion in mafia-infiltrated provinces is larger than in the other group; moreover, there is a change in the trend of the average extortion cases for mafia-infiltrated provinces starting approximately in the year 2004, i.e. after the approval of the public funding for infrastructure as mentioned above.

I use this information to construct the variable λ_{pt}, which measures the share of impacted firms for every province-year. In other words, λ_{pt} measures the extensive

[7]Sectors are defined according to ISIC activity Rev.4.

[8]Industry-level deflators are gathered from the EU KLEMS Growth and Productivity Accounts: 2012 Release.

[9]Firm-level data has been aggregated to maintain confientiality.

[10]Five of these are 2-digits ISIC rev. 4 manufacturing sub-sectors. The remaining ones are 1-digit ISIC rev. 4 sectors.

margin of mafia diffusion. The infiltrated markets are specific industries, located in specific provinces, observed after a given point in time. Therefore λ_{pt} has to be equal to zero in each market that is not defined as mafia-infiltrated. As Figure 3 shows, acts of extortion are also larger than zero in non-infiltrated markets, i.e. in non-mafia provinces and in mafia provinces before mafia arrival. In order to handle this fact and have λ_{pt} equal zero in non-mafia markets, I adopt a "Difference-in-differences" approach and use the increase of reports of extortion registered in the infiltrated provinces after mafia arrival to measure mafia intensity. In particular, I adjust the number of extortion cases observed in every mafia-infiltrated province-year as follows:

$$\tilde{e}_{pt} = \text{mafia province year}_{pt} \times \left[e_{pt} - \left(\bar{e}_{p,PRE} - \bar{e}_{-p,PRE}\right) - \bar{e}_{-pt}\right]$$

where $\tilde{e}_{pt}$ is the adjusted number of extortion cases, $\text{mafia province year}_{pt}$ is a dummy that equals one if the province-year is infiltrated, e_{pt} is the number of extortion cases observed in the raw data, $\bar{e}_{p,PRE}$ and $\bar{e}_{-p,PRE}$ are the averages of reports of extortion from 1998 until year of the approval of the infrastructure in mafia provinces and non-mafia provinces, respectively, and $\bar{e}_{-pt}$ is the yearly average for every mafia-year of the number of extortion cases observed in non-mafia provinces.[11]

Then, I compute the share of impacted firms as follows:

$$\lambda_{pt} = max\left[\frac{\tilde{e}_{pt}}{N_{pt}}, 0\right]$$

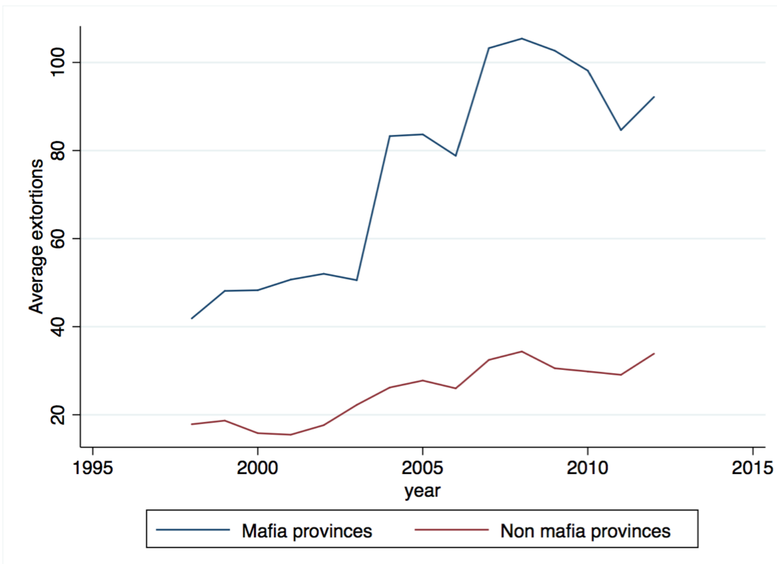
where N_{pt} is the number of firms operating in province p at time t.

In other words, I include in the dataset a variable that measures the share of firms

[11]Notice that some mafia-infiltrated provinces start being infiltrated in 2000. For these provinces, $\bar{e}_{p,PRE}$ and $\bar{e}_{-p,PRE}$ are computed between the years 1998 and 2000. For the remaining mafia-infiltrated provinces, $\bar{e}_{p,PRE}$ and $\bar{e}_{-p,PRE}$ are computed between 1998 and 2002.

impacted in every mafia province-year that equals the number of reports of extortion observed in the specific province-year, adjusted by the difference of the average extortion cases between mafia and non-mafia provinces from 1998 until the year of approval of the renewal works, and adjusted by the average extortion cases in the non-mafia provinces after mafia arrival. If this value is lower than zero, I replace it with zero and I exclude that specific province-year from the analysis.[12]

Figure 3: Sectorial Mafia Presence



Source: computations based on ISTAT yearly book of criminal statistics (ed. 2014).

Note that the way I construct λ_{pt} implies that this paper quantifies the economic consequences of the *increase* of mafia presence studied in Piemontese (2013). Controlling for any other element that influences aggregate outcomes (that can be sector-province specific, province-time specific, sector-time specific or sector specific), mafia infiltrations can be seen as an *extra* bias to the allocative efficiency only of the mafia appealing sectors, located in the infiltrated provinces, after mafia arrival. The analysis that follows relies on this point: I first provide suggestive evidence of a negative

[12]Given that I don't have information on the sectorial intensity of extortion, I assume that mafia groups impact every sector evenly. Thus, in order to obtain the sectorial share of firms that is impacted (λ_{spt}), I divide λ_{pt} by five, i.e. the number of sectors defined as mafia appealing.

correlation between mafia infiltrations and allocative efficiency, then I model the mechanism through which this can happen and use it to quantify the amount of *pizzo* that mafia groups extort from firms and to measure the welfare loss suffered by the infiltrated economies.

The OP decomposition

Before moving to the estimation, it is worth reviewing the OP decomposition of industry-level productivity and describing how it is measured in the present context. The OP decomposition comes from a measure of aggregate efficiency introduced by Olley and Pakes (1996). In this seminal contribution, aggregate productivity is defined as the weighted sum of firms' productivity, where the weight is firms' size. This index can be decomposed into two components: the unweighted average of firms' productivity and the covariance component, which measures the extent to which most productive firms are larger than the less productive ones.

Consider a market populated by N firms. The OP covariance is derived by the following decomposition of the aggregate productivity:

$$\Omega \equiv \sum_{i \in N} \theta_i \omega_i = \bar{\omega} + \sum_{i \in N} ((\theta_i - \bar{\theta})(\omega_i - \bar{\omega})) \tag{1}$$

where Ω is the aggregate productivity of the market, ω_i and θ_i are firm-level productivity and size, respectively, and a "bar" over a variable represents the unweighted average of the firm-level measure.

Thus, the first term of the right hand side $\bar{\omega}$ is the unweighted average productivity of the N firms operating in this market. The second term is the so called OP covariance between productivity and size of the N firms.

Proposition 1 helps to see how the OP covariance contributes to increasing aggregate productivity. The proof is provided in Appendix A.1.

Proposition 1. *Consider the vector ω containing N firm-level productivity ranked as follows $\omega_1 > \omega_2 > \omega_3 > ... > \omega_N$. Consider the vector θ containing N of firm-level size ranked as follows $\theta_I > \theta_{II} > \theta_{III} > ... > \theta_N$.*
If aggregate productivity is defined as the sum of firm-level productivity weighted by firm-level size, the way of maximising it is to have the ranking of firm-level productivity and firm-level size perfectly aligned. In other words, aggregate productivity is maximised when ω_1 is matched to θ_I, ω_2 is matched to θ_{II}, and so forth.

Proposition 1 tells that aggregate productivity is maximised when the rankings of firm-level productivity and firm-level size are perfectly aligned. Looking at the RHS of Equation 1, aggregate productivity is maximised when the OP covariance is maximised (because the first term of the RHS is constant). Hence, the highest value of the OP covariance, which implies aggregate productivity maximisation, is obtained when the most productive firm is also the largest one, the second productive one is the second largest one, and so forth. A market where these rankings are not aligned is a market affected by resource misallocation, which leads to a decrease of aggregate productivity.
In the following section, I motivate this analysis by showing a significant correlation between mafia presence and misallocation. I measure resource misallocation with the OP covariance using (log-) labour productivity, i.e. revenue per worker, and share of employment over total industry employment to measure productivity and size, respectively. These arguments have the advantage that their computation requires information widely available in firm-level datasets and less subject to measurement error than variables such as capital or total factor productivity.

Suggestive evidence

I initially explore the relationship between mafia presence and resource misallocation with a triple Difference-in-differences strategy, which employes the three-dimensional variation of the data, i.e. sector-province-year. I compare the average allocative efficiency of the infiltrated provinces to the one characterising the remaining northern territories, in sectors that are mafia appealing and in the other sectors of the economy, over time. To do so, I estimate the following regression:

$$\text{OPcovariance}_{spt} = \alpha + \sum_t \beta_t(\text{mafia}_{ps} \times \text{year}_t) + \theta_{st} + \theta_p + u_{spt} \tag{2}$$

where the left hand side is the OP covariance in terms of (log) labour productivity and share of employment over total industry employment; mafia_{ps} denotes a dummy that varies at sector-province level and equals one if sector s is mafia appealing and it is located in an infiltrated province p; this dummy is interacted with each available time dummy year_t; θ_p and θ_{st} are province and time fixed effects respectively.

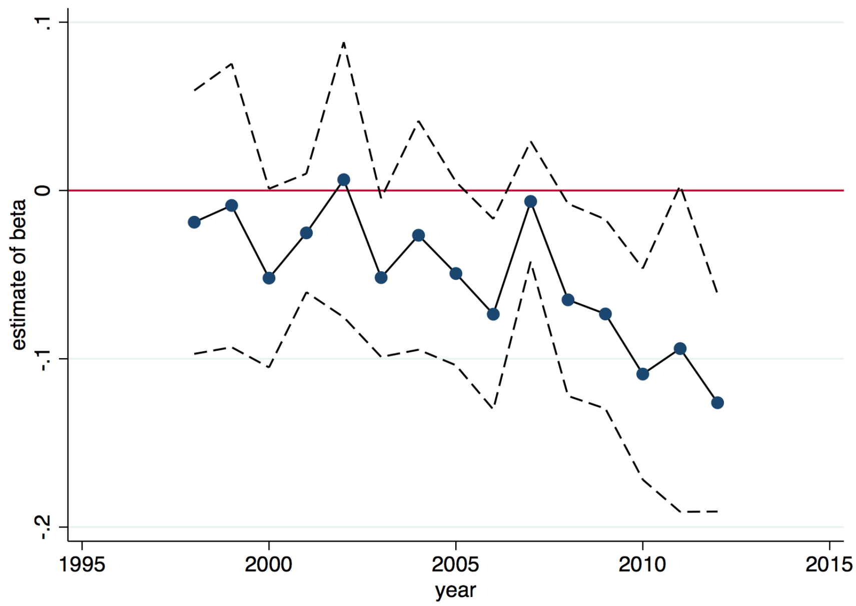
Figure 4 plots the estimates of the β_t's included in Equation 2, i.e. β_{1998}, β_{1999}, ..., β_{2012}, together with their 95% confidence bands. These coefficients follow a decreasing and statistically significant (or marginally significant) trend.[13] These results point to the existence of a negative correlation between mafia presence and allocative efficiency. Interestingly, the decrease of the trend starts around year 2004, i.e. the same time period where the sharp increase in extortion cases happened in the infiltrated provinces, as shown in Figure 3.

In Appendix A.2 I propose a robustness check that allows not only for mafia presence, but also for mafia intensity, which is measured with the data on extortion presented above. The results I obtain corroborate the idea that mafia presence correlates

[13]The magnitude of the estimates is robust to the inclusion of province-year fixed effects. However, most of the betas lose statistical significance, probably because of the sizeable reduction in variation implied by the high number of fixed effects.

negatively with the allocative efficiency of the affected markets. Now that this idea is grounded, the next step is to provide a theoretical explanation of the mechanism through which mafia infiltrations can generate resource misallocation, and exploit it to measure the economic consequences of this phenomenon.

Figure 4: OP covariance in mafia infiltrated markets



Source: Computations based on ISTAT Survey on SMEs and ISTAT yearly book of criminal statistics (ed. 2014).

3 Theoretical framework

Mafia groups affect economic activity by introducing distortions in the functioning of the impacted markets. In particular, *pizzo* extorted from a randomly chosen group of firms alters the allocative efficiency of the infiltrated markets. The regression analysis provided above points to a negative correlation between mafia presence and allocative efficiency. In fact, on average, the OP covariance characterising mafia-infiltrated markets decreases when mafia emerges. However, these estimates tell little about the channel though which idiosyncratic distortions introduced by mafia groups affect resource allocation. Moreover, with a reduced form approach it is not possible to measure the amount of *pizzo* that mafia groups impose on firms.

In this section I outline the theoretical explanation of this mechanism and lay out the basis for the structural estimation of the extorted *pizzo*. I then take advantage of the structural approach to perform a model simulation in order to understand the source of the loss brought by mafia extortion. I also implement a counterfactual analysis where I simulate the northern Italian economy with and without mafia infiltrations. I then compare these two scenarios and quantify the cost that mafia produced in northern Italy.

The way I model how mafia alters the functioning of the economic activity has some features in common with Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Firms are heterogeneous in their level of productivity and face idiosyncratic output distortions. Production units have access to a decreasing return to scale technology and operate in a monopolistic competition framework. Finally, as in Bartelsman et al. (2013), the model includes overhead labour as a part of the technology, to guarantees dispersion of labour productivity even in the absence of mafia distortions.[14]

Consider an economy defined by $p \times t$ labour markets, where each market is defined as a specific geographical area p at a given point in time t. Assume that the final aggregate output Y_{pt} is produced by a representative firm that operates in a perfectly competitive market: the final good is sold at price P, which is taken as given. To produce Y_{pt}, this single representative firm combines s intermediate outputs Y_s produced from all S sectors of the economy in a Cobb-Douglas technology:

$$Y_{pt} = \Pi_{s=1}^{S} Y_s^{\theta_s} \tag{3}$$

[14] Overhead labour can be seen as employment that is not used for production, e.g. personnel for protection, reception, or supportive services.

with $\sum_{s=1}^{S} \theta_s = 1$. Given that the final good price P is taken as given, cost minimisation implies that $P_s Y_s = \theta_s PY$ for every sector s, where P_s is the sector specific price of the intermediate output Y_s.

In each sector s the production of the intermediate output Y_s is carried out by a single representative firm that combines N_s differentiated inputs using a CES production function. Every input Y_{ptsi} is supplied by firm i at price P_{ptsi} in monopolistic competition. Industry s production is given by:

$$Y_{pts} = \left(\sum\nolimits_{i \in N_s} Y_{ptsi}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where σ >1 is the elasticity of substitution between any two varieties. For computational simplicity σ is rewritten as $\frac{1}{1-\gamma}$, with γ <1 yielding:

$$Y_{pts} = \left(\sum\nolimits_{i \in N_s} Y_{ptsi}^{\gamma}\right)^{\frac{1}{\gamma}} \tag{5}$$

From now on, consider a given market defined by industry s located in area p at time t. In this market, as mentioned above, there are N_s firms that produce N_s differentiated products in a monopolistic competition regime.[15] The production function of firm i exhibits decreasing returns to scale, labour is the unique input, and includes overhead labour as friction:

$$Y_i = \Gamma_{pt} A_i (L_i - f_s)^{\alpha} \tag{6}$$

with α smaller than one because of decreasing returns to scale.

I make the following assumptions: (i) firm i's productivity has a firm-specific component A_i, i.e. firm i's total factor productivity (TFP) and a second time-varying and province-specific exogenous component Γ_{pt}, which captures all the province-time

[15] To simplify the notation, given that the focus is on a given market pts, I use the subscript i instead of $ptsi$.

specific factors that affect aggregate outcomes that are common to every industry s located in that area; (ii) the firm-specific productivity component A_i is drawn from a log-Normal distribution with average μ_{ps} and standard deviation σ_{ps}, and these moments of TFP are sector and province-specific but time-invariant, suggesting that different provinces specialise in different sectors;[16] and (iii) overhead labour f_s is exogenously determined and sector-specific.

The mafia enters in the model as an exogenous disturbance on firms' level of output. Given that some firms are coerced and others are not, mafia infiltrations can be seen as idiosyncratic distortions that are orthogonal to firms' individual productivity.[17] This distortion is the result of the interaction between two terms. First, a firm-specific component, called "mafia exposure" parameter τ_i, which is Bernoulli distributed with average λ. This dummy variable equals one if firm i at time t is exposed to mafia infiltrations and zero otherwise. I assume that if τ_i equals one, firm i is forced to pay *pizzo*. If instead τ_i is zero, firm i will not interact with mafia at all. Second, the "mafia intensity" component, which measures the share of output that mafia groups extort, is given by δ. This parameter is assumed to be the same for all firms with τ_i equal to one; i.e. each infiltrated firm pays the same amount of *pizzo* δ.

If the mafia infiltrates the market, firm's i profit is:

$$\Pi_i = (1 - \tau_i \delta) Y_i P_i - w_{st} L_i \tag{7}$$

[16]The log-Normal distribution assumption is consistent with evidence provided by Angelini and Generale (2008) and Donati and Sarno (2015).

[17]This assumption is compatible with the analysis of mafia extortion provided by Balletta and Lavezzi (2014). In fact, the authors model mafia behaviour as a principal-agent model where the criminal organisation does not observe firm-level productivity. Later on, I present two extensions of this model: one where I assume that mafia impact is positively correlated with firm-level productivity and another, demostrating the reverse scenario where the correlation between mafia impact and firm-specific productivity correlate negatively.

where w_{st} is the cost of labour. I assume that w_{st} is exogenous and that it changes over sector and time but not across provinces.[18]

Note that this maximisation problem is static, i.e. there is no link between current profit-maximising decisions and choices made in other time periods. *Pizzo* can be seen as a *one-off* tax, i.e. a payment that is not demanded regularly but on sporadic occasions.

The assumption of monopolistic competition implies that each firm benefits from some degree of market power (given by the parameter γ): firm i supplies its differentiated good at price P_i, which is endogenous to Y_i. As a consequence, profit maximisation yields a price P_i which is a constant markup over the cost of labour:

$$P_i^* = \left[\frac{1}{\gamma}\right]^{\frac{\alpha(1-\gamma)}{1-\alpha\gamma}} \left[\frac{w_{st}}{\alpha}\frac{1}{(1-\tau_i\delta)}\right]^{\frac{\alpha(1-\gamma)}{1-\alpha\gamma}} \left[\frac{1}{\Gamma_{pt}A_i}\right]^{\frac{(1-\gamma)}{1-\alpha\gamma}} \tag{8}$$

Plugging Equation 8 into Equation 7 and maximising with respect to labour yields:

$$(L_i^* - f_s) = \left[\frac{\alpha\gamma}{w_{st}}(1-\tau_i\delta)\right]^{\frac{1}{1-\alpha\gamma}} \left[\Gamma_{pt}A_i\right]^{\frac{\gamma}{1-\alpha\gamma}} \tag{9}$$

Finally, plugging Equation 9 into the production function (Equation 6) yields the following expression of optimal output:

$$Y_i^* = \left[\frac{\alpha\gamma}{w_{st}}(1-\tau_i\delta)\right]^{\frac{\alpha}{1-\alpha\gamma}} \left[\Gamma_{pt}A_i\right]^{\frac{1}{1-\alpha\gamma}} \tag{10}$$

Optimal P_i, Y_i and L_i can be combined to compute firm i's labour productivity as following:

$$LPR_i^* = \frac{P_i^* Y_i^*}{L_i^*} = \left[\frac{w_{st}}{\alpha\gamma}\frac{1}{(1-\tau_i\delta)}\right] - \left[\frac{w_{st}}{\alpha\gamma}\frac{f_s}{(1-\tau_i\delta)L_i^*}\right] \tag{11}$$

[18]This assumption is compatible with the fact that, in Italy, wages are mainly established through collective bargaining. Thus, in every industry, wages are homogeneous at least across the northern regions.

Whereas if mafia groups do not infiltrate the market at hand, firm i's productivity would be:

$$LPR_i^* = \left[\frac{w_{st}}{\alpha\gamma}\right]\left[1 - \frac{f_s}{L_i^*}\right] \tag{12}$$

First of all, notice that the inclusion of overhead labour guarantees that labour productivity varies across firms even in the absence of distortions. Moreover, Equation 12 shows that, in absence of mafia, labour productivity LPR_i^* is increasing in firm size, measured as labour demand L_i^*, and that the firm with the highest value of LPR_i^* is the one with the highest value of L_i^*. This means that in the absence of mafia the most productive firm is also the largest one, and that the resource allocation characterising this market is optimised (see Proposition 1). If, instead, mafia groups infiltrate this market by extorting from a randomly chosen group of firms the share δ of their output, the equilibrium level of labour productivity of firm i is given by Equation 11, from which we can deduce that the statement that the most productive firm is also the largest one is not necessarily true anymore. If this is the case, the ranking alignment of firm-level productivity and firm-level size is distorted. This means that extortion generates resource misallocation and that, according to the description provided in Section 2, the OP covariance is not maximised as it would be in a market where there is perfect correlation between firm-productivity and firm-size.

In the standard model developed in this section, I rationalise what the data described in Section 2 suggests about the relationship between mafia and allocative efficiency, measured with the OP covariance. I now move to the estimation of this model and quantify the amount of *pizzo* imposed by mafia groups in each infiltrated market. I then compute the economic cost suffered by the northern Italian economy because of acts of extortion perpetrated by the mafia.

4 Estimation

In this section, I describe how to bring the model to the data. This structural analysis consists of two main stages. In the first step, I use data on non-infiltrated markets to estimate all the parameters of the model that are unrelated to the mafia. I need these estimates to generate firm-level data and the data on the share of firms that pay *pizzo* described above in order to perform the second part of the empirical analysis. In this stage, I implement the method of simulated moments (MSM henceforth) and, for each sector-province-year that is defined as mafia-infiltrated, I quantify the amount of *pizzo*, i.e. δ_{spt}, that impacted firms are forced to transfer to mafia groups.

I then use the estimates I obtain in both stages to perform two exercises. In the first application I simulate the impact of the mafia on aggregate value added, employment, and average TFP (I do so both by fixing the share of impacted firms and letting δ vary, and fixing δ and letting the share of impacted firms vary). In the second exercise, I conduct a counterfactual analysis where, by comparing the aggregate value added of the infiltrated markets to their simulated counterparts without mafia, I estimate the cost that the northern Italian economy suffered because of mafia infiltrations.

First stage

In this stage, I focus on non-mafia markets. Recall that the three-dimensional variation of the data allows the recognition of a group of N_{NM} markets composed by: (i) sectors that are not appealing for mafia groups, in every northern Italian province, observed during years 1998-2012; (ii) mafia appealing sectors, located in mafia immune provinces, observed during years 1998-2012; (iii) mafia-appealing sectors, in mafia-infiltrated provinces, before mafia arrival, i.e before 2000 for some mafia infiltrated provinces and before 2002 for the remaining provinces.

I use data on these N_{NM} sector-province-year in order to estimate two sets of parameters presented in the theoretical model. The first group contains the parameters related to firm-level productivity, i.e. μ_{ps}, σ_{ps} and Γ_{pt}. The second set includes the exogenous macroeconomic variables, i.e wages w_{st} and overhead labour f_s. According to the assumptions presented in Section 3, firm i's productivity has an idiosyncratic component A_i and second element Γ_{pt}, which is province-year specific. Moreover, the mean and the standard deviation of A_i, namely μ_{ps} and σ_{ps}, of firms located in province p belonging to sector s are time invariant. Finally, overhead labour f_s is sector-specific and wages w_{st} are sector-specific and vary over time.

The three-dimension structure of the data and the assumptions stated in the model allow me to use non-mafia markets as the best counterfactual of infiltrated markets without mafia. In fact, I utilise information on mafia appealing sectors located in mafia impacted provinces before mafia arrival to estimate μ_{ps} and σ_{ps}. I compute Γ_{pt} with data on sectors that are not mafia-appealing. Finally, sectorial wage w_{st} and overhead labour f_s are estimated with data on non-mafia provinces and mafia-infiltrated provinces before mafia arrival.

In order to compute these parameters, I follow the theoretical framework presented in Section 3 and start from the firm-level optimal solution for value added. Firm i's value added is the product of its optimal price and output, shown in Equations 8 and 10 respectively.

$$VA_i^* = \left[\frac{\alpha\gamma}{w_{st}}\right]^{\frac{\alpha}{1-\alpha\gamma}} \left[A_i \Gamma_{pt}\right]^{\frac{\gamma}{1-\alpha\gamma}} \tag{13}$$

Consequently, firm i's log-value added is:

$$\log(VA_i^*) = \frac{\alpha}{(1-\alpha\gamma)}\left[\log(\alpha\gamma) - \log(w_{st})\right] + \frac{\gamma}{(1-\alpha\gamma)}\left[\log(A_i) - \log(\Gamma_{pt})\right] \tag{14}$$

An expression for value added as a function of optimal labour can be derived using Equations 11 and 9:

$$VA_i^* = \frac{1}{\alpha\gamma} w_{st}(L_i^* - f_s) \tag{15}$$

Moving from firm-level optimal solutions to aggregate results, I compute the average and the variance of the log-value added for each of the N_{NM} mafia-free market as follows:

$$\overline{\log(VA)}_{spt} = \frac{\alpha}{(1-\alpha\gamma)}\left[\log(\alpha\gamma) - \log(w_{st})\right] + \frac{\gamma}{(1-\alpha\gamma)}\log(\Gamma_{pt}) + \frac{\gamma}{(1-\alpha\gamma)}\tilde{\mu}_{A_{ps}} + \epsilon^1_{spt} \tag{16}$$

where $\tilde{\mu}_{A_{ps}}$ is the mean of $\log(A_i)$ that is province-sector specific.

$$\mathrm{VAR}(\log(VA))_{spt} = \left[\frac{\gamma}{(1-\alpha\gamma)}\right]^2 \tilde{\sigma}^2_{A_{ps}} + \epsilon^2_{spt} \tag{17}$$

where $\tilde{\sigma}^2_{A_{ps}}$ is the variance of $\log(A_i)$ that is province-sector specific.
As a third condition, I use the average of value added as a function of labour:

$$\overline{VA}_{spt} = \frac{1}{\alpha\gamma} w_{st}(\overline{L}_{spt} - f_s) + \epsilon^3_{spt} \tag{18}$$

I can estimate the parameters μ_{ps} and σ_{ps} for each sector-province, Γ_{pt} for each province-year, w_{st} for each sector-year and f_s for each sector, by solving the system of $3 \times N_{NF}$ equations denoted by equations 16, 17 and 18. In fact, for each of the N_{NM} mafia-free sector-province-year, I observe $\overline{\log(VA)}$, $\mathrm{VAR}(\log(VA))$, $\overline{VA}$, i.e. the dependent variables of the system, and $\overline{L}$ that will be used as a regressor. Moreover, I assume specific values of α and γ.[19]
This system of equations can be solved using OLS estimation. In fact, μ_{ps}, Γ_{pt} and w_{st} can be estimated from the sector-province, province-time and sector-time fixed

[19] I follow Bartelsman et al. (2013) and Bloom (2009) and assume a 20 percent markup that yields γ equal to 0.83. Moreover I introduce additional curvature to the firm-level profit function and assume α equal to 0.85 as in ak2 (2005).

effects in Equation 16, while Equation 17 serves to estimate σ_{ps}. Estimates of the sectorial time-varying wage $\widehat{w}_{st}$ are then plugged into Equation 18, whose estimation yields $\widehat{f}_s$.[20]

As a final remark, it is worth mentioning that the estimates obtained at this stage are robust to two alternative specifications of the systems. In the first one I use average labour, variance of labour, and average value added as a function of labour for every non-mafia province-sector-years. In the second alternative, I estimate a system of $5 \times N_{NF}$ equations, where I add to the baseline system average and variance of labour for each non-mafia sector-province-year. The results I obtain in both alternatives are strongly correlated to the estimates that the baseline system yields.

Second stage

The second stage of the analysis focuses on the mafia-infiltrated markets, defined as mafia appealing sectors, located in mafia-infiltrated provinces, observed after the arrival of mafia. For each of these N_M markets, I estimate the amount of *pizzo* that mafia groups extort from a randomly chosen group of firm by performing the MSM. The set of parameters that I compute in this stage is the vector Δ, which includes the N_M values of δ_{spt} that mafia groups extort in each infiltrated market.

Given that mafia distortion cannot be disentangled using aggregate data, I cannot estimate vector Δ using standard econometrics techniques. Thus, I compute it using MSM, which minimises a distance criterion between key moments from actual data and corresponding moments computed using simulated data.

For every sector-province-year, I generate a vector of firm-specific productivity A_i from a log-Normal distribution with average $\widehat{\mu}_{ps}$ and standard deviation $\widehat{\sigma}_{ps}$.[21] Firm-specific productivity is then rescaled with the province-year component $\widehat{\Gamma}_{pt}$.

[20]Alternatively, this system of $3 \times N_{NF}$ can be solved simultaneously through MLE. In fact, linearity guarantees that the estimates obtained using OLS are equivalent to the ones obtained performing MLE.

[21]The length of this vector is the number of firms that operate in the specific sector-province-year

Then, I let mafia groups enter in the model. Recall that mafia impact is modelled as an idiosyncratic distortion constituted by the interaction of the "mafia exposure" component τ_i with the "mafia intensity" component δ. The "mafia exposure" component is assumed to follow a Bernoulli distribution with average λ. Hence, in each mafia-infiltrated market, λ gives the share of firms that are impacted by mafia groups. The computation of λ characterising each impacted market is described in detail in Section 2. Mafia infiltrations are orthogonal to firms' productivity, thus I randomly select the share λ of firms that have to pay the tax δ, which I estimate structurally through MSM. In other words, I feed the model with actual data on a component of the distortion, i.e. the average λ of τ_i, in order to measure the other component δ, which is unobserved.[22]

I implement the MSM as follows: I create a grid Θ of values that δ can take and choose a set of observed data moments Φ^O that the model has to match.[23] For each possible vector Δ formed by each possible combination of values of δ in Θ, the model is solved and the simulated moments of interest $\Phi(\delta)^S$ are computed. The estimate of the vector containing the amount of *pizzo* paid in each mafia-infiltrated market $\widehat{\Delta}$ is derived according to the following criterion:

$$\widehat{\Delta} = \arg\min_{\Delta}[\Phi^O - \Phi(\Delta)^S]' W [\Phi^O - \Phi(\Delta)^S] \tag{19}$$

where W is a weighting matrix.[24]

The most important actual data moment that I use in this analysis is the OP covariance between productivity and size. In fact, this analysis relies on the assumption that mafia extorting behaviour generates factor misallocation, and hence reduces

[22]In a way, this approach speaks to Ranasinghe and Restuccia (2018) who try to understand the role of crime and financial market development as sources of misallocation, using actual data on these frictions.

[23]The grid search method is useful to avoid convergence problems with possible non-convexities of the objective function (see Equation 19).

[24]For a comprehensive description of the functioning of MSM and of its statistical properties see **?**.

aggregate productivity in mafia-infiltrated markets and that can be detected by looking at the OP covariance that characterise the affected sector-province-year. Any other factor that contributes to aggregate productivity is estimated using data on mafia-free environments.[25] I add to the set of actual data moments the average and the variance of labour characterising each mafia-infiltrated market to estimate an overidentified model.

5 Results

This section presents and discusses the results obtained from the estimation described in Section 4. As illustrated above, the mafia infiltrates markets by forcing a randomly selected group of firms to pay *pizzo*, i.e. imposing a tax δ on firm i's output. I use the MSM to estimate the vector Δ containing the amount of *pizzo* imposed in each infiltrated market. The structural approach allows me to go beyond the mere estimate of Δ and to perform two relevant exercises. First, a model simulation aimed at understanding the source of the overall economic costs imposed by the mafia. Second, a counterfactual analysis that quantifies this cost.

I simulate the impact of extortion in each mafia sector on aggregate value added and employment, and average TFP, changing both the extensive and the intensive margins of this distortion. I find that mafia infiltrations can reduce the number of firms that operate in the impacted markets, because some impacted firms can incur negative profits, and thus they have to leave the market. Moreover, by extorting *pizzo*, mafia groups make the coerced firms reduce employment, and, in turn, production. This economic cost, which is increasing with the imposed mafia-tax δ, is thus composed by the transfer of money that extorted firms have to make, the forgone value added of the impacted firms that exit the market because they incur

[25] Recall that I provide some suggestive evidence of the reliability of this point in Section 2, where I show that the OP covariance of the mafia appealing sectors located in mafia appealing provinces decrease after mafia arrival.

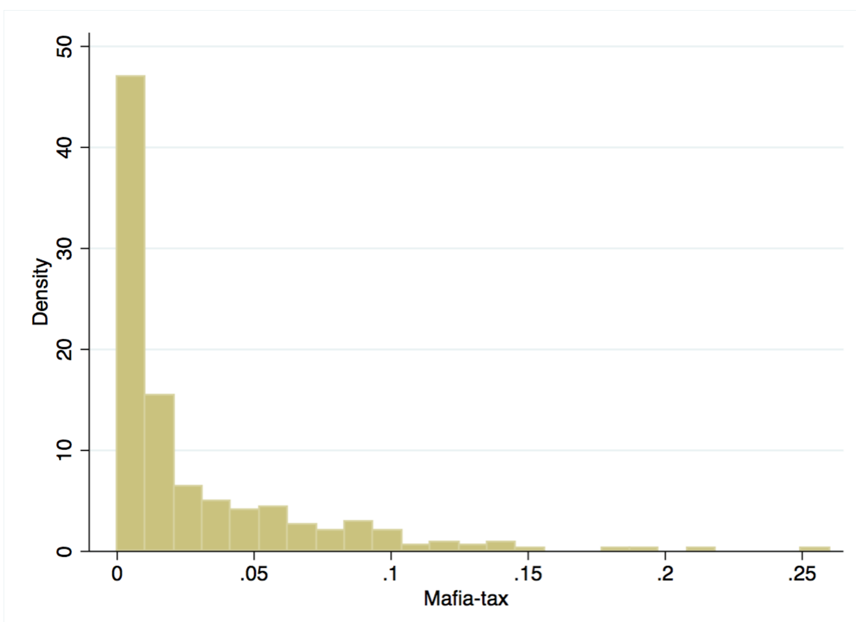
negative profits, and the forgone value added of the impacted firms that have to reduce employment. The last two components, which account for approximately three-fourths of the total cost, can be seen as the welfare loss due to mafia infiltrations. I measure this cost with the counterfactual analysis, in which I compare the aggregate value added of the infiltrated economy to the one that would have been without the mafia, i.e. by setting the share of impacted firms λ equal to zero.

5.1 Model estimation

Figure 5 plots the histogram of the estimates of *pizzo*, i.e. $\hat{\delta}$.[26] The distribution is right-skewed, with most of the estimates ranging between 0.01 and 0.05. This means that in most of the infiltrated markets, impacted firms are forced to pay an extortion that ranges between 1 and 5 percent of their output.

Another way of studying the results is by looking at Table 1, which reports the

Figure 5: Amount of extortion δ



average of $\hat{\delta}$ computed for each mafia appealing sector s. The least impacted sector

[26]A brief comment on the fit of the model is provided in Appendix A.3.

is wholesale and retail trade with average *pizzo* of 1%. Construction and services have an average *pizzo* of 3%, while community social and personal services has a slightly higher average tax of 5%. The most impacted sector is accommodation and food services, where the average *pizzo* is 8%. All in all, these estimates suggests that on average, depending on the sector where they operate, impacted firms are extorted between 1 and 8 percent of their output.[27]

Table 1: Mafia-tax on output

Sector	Average by sector	Number of markets
Construction	3%	81
Wholesale and retail trade	1%	81
Accommodation and food services activities	8%	79
Services	3%	81
Community social and personal services	5%	81

Estimates of δ are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estate and Firms Confiscated from Criminal Organisation (ANBSC). Results come from the application of the Method of Simulated Moments (MSM) through a grid search. δ takes values from a grid bounded between 0 and 0.5.

Table 2 reports the results of a crucial validation exercise, where I estimate the amount of *pizzo* in the seven non-mafia sectors located in the mafia-infiltrated provinces after mafia arrival. In other words, assuming that mafia groups infiltrate also sectors that are not defined as mafia appealing, I estimate the amount of extortion imposed in this environment. First of all, I compute the parameters necessary to generate firm-level data, using information on the new control group. Wages w_{st} and overhead labour f_s are measured using data on non-infiltrated mafia provinces. Mean and standard deviation of TFP, $\mu_{A_{ps}}$ and $\sigma_{A_{ps}}$, are computed with

[27] It is worth to mentioning that these numbers are compatible with those presented by Balletta and Lavezzi (2014). The authors use a unique dataset on extortion in Sicily in which *pizzo* rate is observed. The reported magnitudes of *pizzo* (Figure 9 pg. 18) are on average even higher than the estimates obtained in the present analysis.

data on mafia sectors-provinces before mafia arrival. In order to estimate the productivity component common to all firms that operate in the same province-time, Γ_{pt}, I need information on non-mafia sectors. Since, in this exercise, every sector is infiltrated by mafia, I compute Γ_{pt} performing seven rounds of the first stage of the estimation (one per sector), each one including non-appealing sector within the group of mafia-appealing sectors. Using these parameters, I can perform the second stage of the estimation, where I match the OP covariance simulated by the model to the corresponding one observed in the data, and I back out one δ for each affected market.

The results presented in Table 2 validate this placebo test. In fact, for each mafia non-appealing sector, average estimates of δ are very close to zero. This means that the allocative efficiency characterising each market is entirely explained by factors that are province-sector, province-time, sector-time and sector specific, and not by acts of extortion imposed by the mafia.

Table 2: Mafia-tax on output

Sector	Average by sector	Number of markets
Food, beverages, tobacco	0.1%	80
Texiles	0.4%	80
Wood, Paper	0.3%	78
Chemicals	0.1%	81
Machinery	0.1%	81
Others	0.4%	80
Transportation and storage	0.2%	78

Estimates of δ are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estates and Firms Confiscated from Criminal Organisation (ANBSC). Results come from the application of the Method of Simulated Moments (MSM) through a grid search. δ takes values from a grid bounded between 0 and 0.5.

5.2 Model simulation and counterfactual analysis

In order to understand where the economic loss due to mafia infiltration derives, I perform two simulation exercises of the baseline model described in Section 3. In the first test, I focus on the intensive margin of the distortion, studying how aggregate outcomes change by keeping the number of infiltrated firms fixed and changing the amount of *pizzo* they are forced to pay. The second simulation considers the reverse exercise, i.e. the intensive margin of the distortion. I look at aggregate outcomes, fixing the amount of *pizzo* and changing the share of impacted firms, and I explain the composition of cost that extortion brings to the infiltrated economy. Finally, I perform a counterfactual analysis that quantifies this cost.

The intensive margin of the mafia

In this exercise, I simulate five economies, one for each mafia sector. I simulate a market with 1000 firms, choosing parameters obtained in Stage 1 (Section 4) as follows: (i) for every sector, the mean and the standard deviation of TFP are the median values of the estimates of $\widehat{\mu}_{ps}$ and $\widehat{\sigma}_{ps}$ repsectively; (ii) the province-year component of firms' productivity is the median of $\widehat{\Gamma}_{pt}$ for year 2006; (iii) the sectorial wage $\hat{w}_{st}$ is the estimate obtained for year 2006; and (iv) the overhead labour $\hat{f}_s$ is the one obtained for the sector at hand.[28] I hold the share of impacted firms λ_{pt} constant at its median level observed in year 2006 and I let the amount of *pizzo* δ change between zero and one. Then, for each value of δ, I compute the total number of active firms (i.e. those that do not incur negative profits), their average TFP, and the aggregate value added and employment. Each simulation is repeated 25000 times.

Recall that firm i extracts its value of TFP A_i from a log-Normal distribution and its value of the "mafia exposure" parameter τ_i (i.e. the idiosyncratic component of

[28]Comparable results are obtained with different parameters combinations and baseline years.

the distortion) from a Bernoulli distribution. This means that firm i knows its level of productivity and whether it is forced to pay the tax δ. Given that the only input that firm i utilises is labour, whose price (wage) is taken as given, its draws of A_i and τ_i are enough to determine whether it produces or not. In other words, if firm i is extorted the share δ of its output two alternatives are possible: (i) it hires less workers and produces less; or (ii) if its draw of A_i is too low, its profit is negative and it stays inactive. This fact has three implications. First of all, aggregate employment and aggregate value added decrease with δ. In fact, recall from Equations 20 and 21 below that both optimal labour and equilibrium value added depend negatively on the magnitude of the extortions.

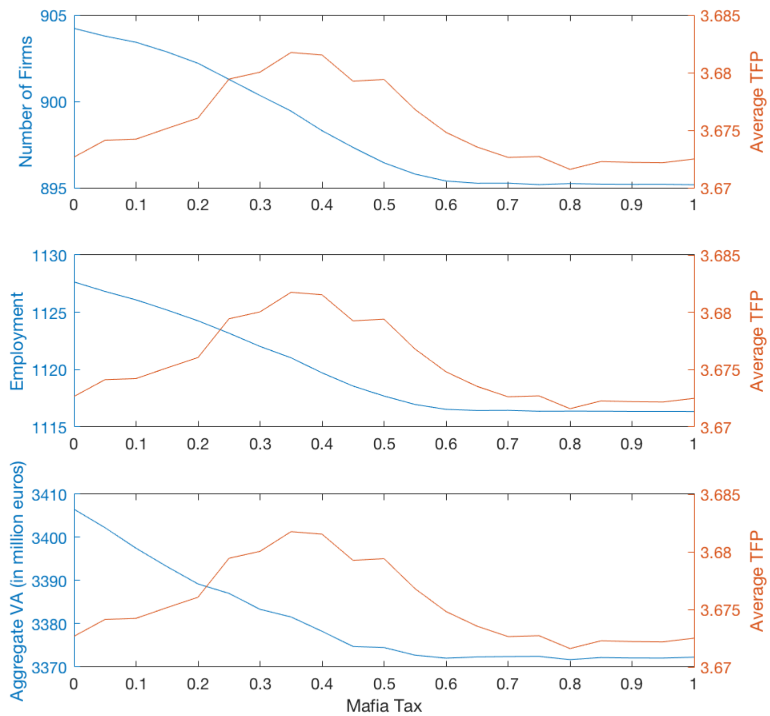
$$(L_i^* - f_s) = \left[\frac{\alpha\gamma}{w_{st}}(1 - \tau_i\delta)\right]^{\frac{1}{1-\alpha\gamma}} [\Gamma_{pt} A_i]^{\frac{\gamma}{1-\alpha\gamma}} \tag{20}$$

$$VA_i^* = \left[\frac{\alpha\gamma}{w_{st}}(1 - \tau_i\delta)\right]^{\frac{\alpha\gamma}{1-\alpha\gamma}} [\Gamma_{pt} A_i]^{\frac{\gamma}{1-\alpha\gamma}} \tag{21}$$

Second, given that the impacted firms that incur negative profits exit the market, there will be a lower number of operating firms than in the corresponding scenario without mafia infiltrations. Third, it is possible that the average TFP of the operating firms increases with *pizzo*, because the productive units that exit are those with lower draws of TFP.

Figure 6 presents the outcome of the construction industry. These results confirm the premise discussed above. The first panel of Figure 6 shows that as δ increases, the number of firms that produce in the market decreases. The second and the third panels show that both total employment and aggregate value added decrease as δ increases. Interestingly, we can notice that average TFP is inverse-U shaped, i.e. it increases up to a given threshold of δ and then it starts decreasing. This might be due to the fact that when the rate at which firms are taxed is too high, both firms with high and low draws of TFP are unable to produce, and mafia simply removes a portion of firms from the market.[29]

Figure 6: Model simulation



The extensive margin of the mafia

The simulation presented above highlights that the welfare loss brought by the mafia depends on the forgone production of the infiltrated firms that either reduce employment, or do not produce at all. To have a taste of the magnitude of these components, I perform a second simulation. I generate firm level data with the same parameters of the previous application, but here, for each sector, I fix the mafia tax δ at its average level (values presented in Table 1) and I make the share of impacted firms λ vary between zero and one. I focus on infiltrated firms and, for each value of λ, I compute: (i) the total amount of *pizzo* paid by the firms that do not exit the

[29]The same exercise is repeated for the remaining mafia appealing sectors. Results, available upon request, are analogous to the ones obtained for the construction sector.

market —this is not a component of the welfare loss but simply a waste of resources; (ii) the total forgone value added of the firms that reduced employment; and (iii) the forgone value added of the firms that leave the market. I also compute the average TFP of the firms that produce in each scenario, i.e. for every value of λ.

Figure 7 plots the results for the construction industry.[30] The cost, which is the sum of (i), (ii) and (iii), is clearly increasing with the share λ of impacted firms. Quite remarkably, the welfare loss, i.e. the forgone value added due to either employment reduction or exit, accounts for almost three fourths of the total cost. This is a key result of the paper; in fact, the model developed here provides a way not only to estimate the amount of resources extorted, but also to uncover the welfare loss beyond them, which is almost three times higher than the mere transfer to mafia groups.

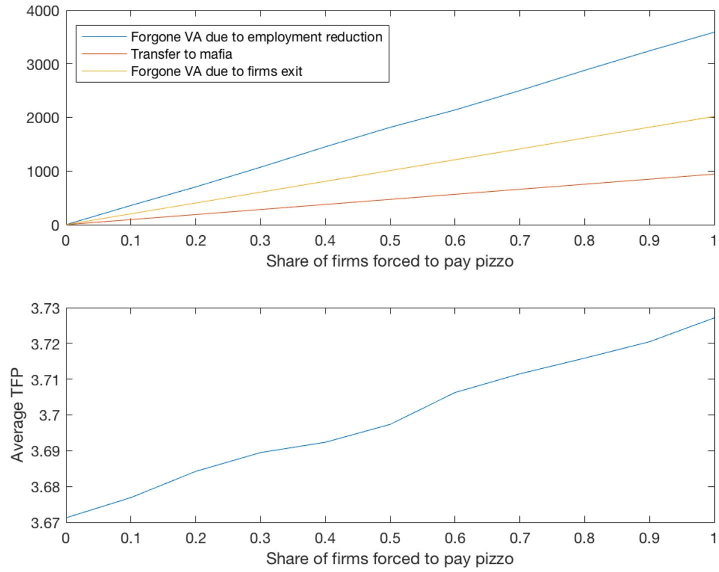
Finally, the second panel of Figure 7 shows that TFP is steadily increasing. This result suggests that imposing a relatively small *pizzo*, makes only the least productive firms exit the market, implying an increase of the average TFP of the producing firms.

Counterfactual analysis

The previous subsection sheds light on the sources of the economic cost due to extortion. To quantify this cost, I implement a counterfactual analysis where each infiltrated market is compared to its corresponding scenario without mafia infiltrations, i.e. where λ is set equal to zero. For each market, I compute the three components of the cost explained above, i.e. the total transfer to mafia and the forgone value added due to both reduction in employment and firms' exit. Results are aggregated by sector in Table 3. The most heavily impacted sector is Accommodation and food services, with a total cost of more than 800 million euros, while

[30] Results obtained from the simulation of the other mafia-appealing sectors are comparable to the ones presented. Figures are available upon request.

Figure 7: Model simulation



the least impacted is Services, with a total cost of approximately 340 million euros. The total cost suffered by northern Italy is approximately 2.5 billion euros. Only one-fourth of this cost is the transfer obtained by mafia groups. The remaining three-fourths account for the welfare loss due to the reduction in production carried out by the infiltrated firms.

Table 3: Loss of value added due to mafia (in million euros)

Sector	Forgone value added	Transfer	Total cost
Construction	311.08	110.44	421.52
Wholesale and retail trade	313.62	107.35	420.97
Accommodation and food services activities	601.18	217.87	819.05
Services	251.15	90.09	341.24
Community social and personal services	379.14	134.60	513.74
Total	1856.17	660.35	2516.52

Results are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estates and Firms Confiscated from Criminal Organisation (ANBSC). Column "Forgone value added" is computed by aggregating the forgone value added due to employment reduction and to firm exit in each sector. Column "Transfer" collects the *pizzo* payed by each impacted firm in each sector. Column "Total cost" reports the sum of "Forgone value added" and "Transfer".

6 Alternative specifications

This section considers two extensions of the model presented in Section 3. First, mafia impact is assumed to be positively correlated with firm-level productivity. In other words, the probability that a firm is asked to pay *pizzo* increases with its level of TFP. The second specification examines the reverse scenario, in which mafia targeting is negatively correlated with firm-level productivity.

Positively correlated distortions

In this scenario, the only deviation from the baseline model concerns the assumption on the relationship between the mafia targeting and firm-level TFP. Indeed, in this case, the distribution of mafia-related distortions is assumed to be positively correlated with firm i's draw of A_i. Specifically, firms can be ranked according to their individual probability of being impacted by mafia and this probability correlates positively with firm-level TFP. In each mafia-infiltrated market, firm i's maximisation problem can be rewritten as:

$$\Pi_i = (1 - \tilde{\tau}_i \delta) Y_i P_i - w_{st} L_i \tag{22}$$

The idiosyncratic component of the distortion, i.e. the "mafia exposure" parameter $\tilde{\tau}_i$, is now an interaction between two terms: (i) τ_i that is Bernoulli distributed with average λ (the observed share of firms that are forced to pay *pizzo*); and (ii) ζ_i that also follow a Bernoulli distribution, where the probability that ζ_i equals one increases with A_i, i.e. $\frac{\partial \mathrm{P}(\zeta_i = 1)}{\partial A_i} > 0$. This interaction guarantees that the share of firms impacted by the mafia is exactly the share observed in the data. I estimate the model following the steps described in Section 4. Table 4 shows the obtained results. The estimates of *pizzo* are comparable to the ones obtained in the baseline model.

Table 4: Positive correlation between mafia targeting and firm-level TFP

Sector	Average by sector	Number of markets
Construction	2%	81
Wholesale and retail trade	1%	81
Accommodation and food service activities	7%	79
Services	3%	81
Community social and personal services	3%	81

Estimates of δ are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estates and Firms Confiscated from Criminal Organisation (ANBSC). Results come from the application of the Method of Simulated Moments (MSM) through a grid search. δ takes values from a grid bounded between 0 and 0.5.

Negatively correlated distortions

The second alternative specification considers the reverse assumption: mafia targeting and firm-level TFP are negatively correlated. Firms that operate in mafia-infiltrated markets maximise profit given by Equation 22. However, in this case, the "mafia exposure" parameter $\tilde{\tau}_i$ is the interaction between τ_i and γ_i, where the probability of being impacted by the mafia decreases with the firm-specific draw of A_i, i.e. $\frac{\partial \mathrm{P}(\gamma_i=1)}{\partial A_i} < 0$. Table 5 shows the obtained results, which are comparable to the ones estimated in the baseline model.

Table 5: Negative correlation between mafia targeting and firm-level TFP

Sector	Average by sector	Number of markets
Construction	3%	81
Wholesale and retail trade	1%	81
Accommodation and food services activities	9%	79
Services	4%	81
Community social and personal services	5%	81

Estimates of δ are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estates and Firms Confiscated from Criminal Organisation (ANBSC). Results come from the application of the Method of Simulated Moments (MSM) through a grid search. δ takes values from a grid bounded between 0 and 0.5.

6.1 Model simulation and counterfactual analysis of the alternative specifications

In order to understand the composition of the cost due to mafia infiltrations in these alternative specifications, I perform the model simulation described above ("The extensive margin of the mafia"), in which I fix the value of *pizzo* δ and I let vary the share of impacted firms λ between zero and one. I focus on infiltrated firms and, for each value of λ, I compute: (i) the total amount of *pizzo* paid by the firms that do not exit the market; (ii) the total forgone value added of the firms that reduced employment; and (iii) the forgone value added of the firms that leave the market.

Results are presented in Figure 8. The first panel of the figure reports the outcome of the simulation of the first scenario, where there is positive correlation between firms' productivity and probability of being coerced by the mafia. In this framework, the forgone value added due to employment reduction accounts for more than one half of the total cost, while the forgone value added due to firms' exit is not even one-fourth of the total cost. Reasonably, if mafia groups prefer to extort more productive firms, the impacted firms are more likely to reduce employment, and, in turn, produce less, than to incur negative profits, and, thus, exit the market. Instead, if mafia distortion is negatively correlated with firms' productivity, impacted firms are more likely to exit the market. This fact is highlighted in second panel of Figure 8, in which it can be noticed that the forgone value added due to firms' exit is higher than the previous case, accounting for more than one-third of the total cost.

In order to measure the magnitude of the total cost due to mafia infiltrations, I perform the same counterfactual analysis described in Section 5, where each infiltrated market is compared to its corresponding scenario without mafia infiltrations, i.e. where λ is set equal to zero. For each market, I compute the three components of the cost, i.e. the total transfer to mafia and the forgone value added due to both reduction in employment and firms' exit. Table 6 reports the results. By impacting firms in the upper tail of the TFP distribution mafia groups generate a total cost of approximately 4 billion euros. Not surprisingly, this cost is higher than the one computed in the baseline model, which is around 2.5 billion euros, and the one computed assuming negatively correlation between mafia targeting and productivity, which is approximately 1.8 billion euros.

Figure 8: Model simulation

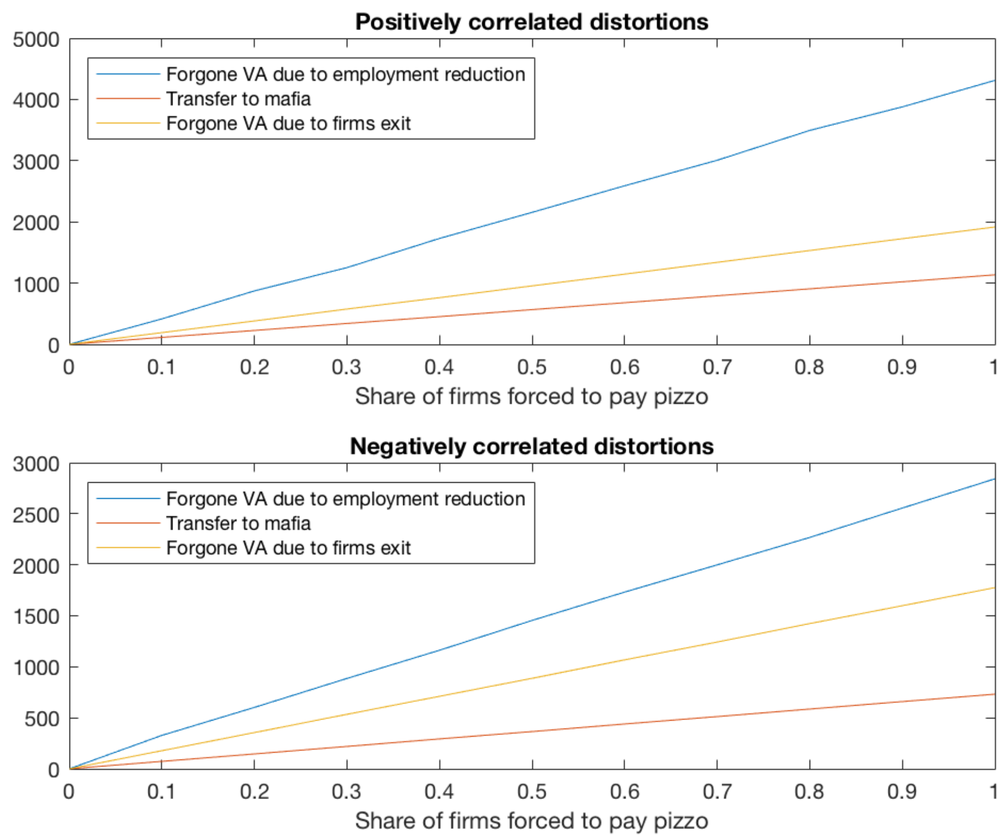


Table 6: Loss of value added due to mafia (in million euros)

Sector	Forgone value added	Transfer	Total cost
Positively correlated distortions			
Construction	515.74	175.35	691.09
Wholesale and retail trade	521.32	172.03	693.35
Accommodation and food service activities	991.56	277.64	1,269.19
Services	418.58	104.65	523.23
Community social and personal services	630.23	220.58	850.81
Total	3,077.47	950.25	4,027.66
Negatively correlated distortions			
Construction	242.64	67.94	310.57
Wholesale and retail trade	241.48	62.79	304.27
Accommodation and food service activities	456.90	123.36	580.26
Services	195.90	52.89	248.80
Community social and personal services	295.73	82.81	378.54
Total	1,432.73	389.79	1,822.52

Results are obtained using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT, data from the yearly Book of Criminal Statistics published by ISTAT and information provided by the National Agency for the Administration and Management of Real Estate and Firms Confiscated from Criminal Organisation (ANBSC). Column "Forgone value added" is computed by aggregating the forgone value added due to employment reduction and to firm exit in each sector. Column "Transfer" collects the *pizzo* payed by each impacted firm in each sector. Column "Total cost" reports the sum of "Forgone value added" and "Transfer".

7 Concluding remarks

Despite the considerable attention and the many efforts that have been made in studying the development and the functioning of organised crime, the nature and the magnitude of the economic cost of this phenomenon is still a topic of active research. This paper tries to answer this question by proposing a new estimation approach that integrates tools from panel data analysis and structural econometrics. I study the economic consequences of mafia diffusion in northern Italy. In particular, I focus on the relationship between extortion, a typical mafia activity, and allocative efficiency.

I first explore whether there is any correlation between mafia diffusion and allocative efficiency. By looking at how the OP covariance between size and productivity characterising the infiltrated sectors and territories changes after mafia arrival, I show that there is a significant correlation between mafia presence and resource misallocation. I then theorise this mechanism: using a simple model of monopolistic competition I prove that acts of extortions generate misallocation, by introducing distortions in the alignment of the rankings of firm-level productivity and firm-level size.

The key insight of this paper is the methodology developed to measure the amount of *pizzo*. This method uses panel data that vary across sector-province-year in a structural model of resource misallocation. The fact that only specific sectors of the economy, located in specific provinces, observed after a given point in time, are defined as infiltrated, enables to use information on the non-infiltrated markets to estimate all the factors that explain allocative efficiency beyond the mafia, which are common to infiltrated and non-infiltrated markets. These parameters and actual data on mafia diffusion are then used to estimate the *extra element* that affects only the allocative efficiency of the infiltrated markets, i.e. the amount of *pizzo*.

This method delivers estimates of the average sectorial *pizzo* that ranges between 1 and 8 percent of the output level of the taxed firms. The counterfactual analysis performed using these estimates, which compares the aggregate value added of the infiltrated markets to that which would have been without the mafia, measures the total cost suffered by the northern Italian economy during years 2000-2012. This cost is approximately 2.5 billion euros. A crucial result of this analysis, which goes beyond the quantification of *pizzo* and of the cost of the mafia, is that the resources that mafia groups coerce from the impacted firms account for only one-fourth of the total cost. Therefore, the extortion of resources that would otherwise have been used productively, implies a welfare loss that, in monetary terms, is three times higher than the total amount of *pizzo* that mafia groups receive. Understanding the magnitude of the loss entailed by extortion, which goes beyond the revenue that mafia groups make, would therefore be relevant for the policymaker.

In conclusion, this paper proposes new insights into the economic consequences of the Italian mafia. Moreover, it opens a methodological debate on how to use structural models to give sense to panel data.

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A Appendices

A.1

This appendix contains the proof of Proposition 1 introduced in Section 2.

Proposition 1 *Consider the vector ω containing N firm-level productivity ranked as follows $\omega_1 > \omega_2 > \omega_3 > ... > \omega_N$. Consider the vector θ containing N of firm-level size ranked as follows $\theta_I > \theta_{II} > \theta_{III} > ... > \theta_N$.*
If aggregate productivity is defined as the sum of firm-level productivity weighted by firm-level size, the way of maximising it is to have the ranking of firm-level productivity and firm-level size perfectly aligned. In other words, aggregate productivity is maximised when ω_1 is matched to θ_I, ω_2 is matched to θ_{II}, and so forth.

Proof. Consider two elements of ω, $\omega_1 > \omega_2$, and two elements of θ, $\theta_I > \theta_{II}$. To prove Proposition 1, Equation 23 must be true:

$$\omega_1\theta_I + \omega_2\theta_{II} > \omega_1\theta_{II} + \omega_2\theta_I \tag{23}$$

Given that $\omega_1 > \omega_2$, ω_1 can be written as follows: $\omega_1 = \omega_2 + \Delta\omega$ (with $\Delta\omega > 0$). For the same reasoning $\theta_I = \theta_{II} + \Delta\theta$ (with $\Delta\theta > 0$). Plugging these expressions into Equation 23 and rearranging we obtain:

$$(\omega_2 + \Delta\omega)(\theta_{II} + \Delta\theta) + \omega_2\theta_{II} > (\omega_2 + \Delta\omega)\theta_{II} + \omega_2(\theta_I I + \Delta\theta)$$

$$\omega_2\theta_{II} + \Delta\omega\Delta\theta + \Delta\omega\theta_{II} + \Delta\theta\omega_2 + \omega_2\theta_{II} > \omega_2\theta_{II} + \Delta\omega\theta_{II} + \omega_2\theta_{II}\Delta\theta\omega_2$$

That leads to:

$$\Delta\omega\Delta\theta > 0$$

which is always true.

Pick two other elements from vector ω and vector θ, such that $\omega_A > \omega_B$ and $\theta_C > \theta_D$.

Given the computations provided above, we know that:

$$\omega_A\theta_C + \omega_B\theta_D > \omega_A\theta_D + \omega_B\theta_C \tag{24}$$

therefore:

$$\omega_1\theta_I + \omega_2\theta_{II} + \omega_A\theta_C + \omega_B\theta_D > \omega_1\theta_{II} + \omega_2\theta_I + \omega_A\theta_D + \omega_B\theta_C \tag{25}$$

We can apply this reasoning to every element of vector ω and vector θ. $\square$

A.2

This appendix introduces some robustness checks of the motivated evidence presented in Section 2, where I show that mafia *presence* correlates negatively with allocative efficiency. The main point here is to show that mafia *intensity* correlates negatively with allocative efficiency. To show this point I implement the following IV strategy. Equation 26 describes the core specification of the model.

$$\text{OP covariance}_{spt} = \alpha + \beta \text{Mafia intensity}_{spt} + \eta_p + \theta_{st} + u_{spt} \tag{26}$$

The outcome variable is the OP covariance between size and productivity computed for every sector s province p and year t. Mafia intensity is measured through the interaction between "extortion cases per 1000 firms", reported in each province p and year t, and a dummy variable that equals one if sector s is classified as mafia-appealing. Mafia intensity is instrumented with a dummy that takes a value of one if the market is defined as mafia-infiltrated, according to the definition introduced in Section 2.[31] The core specification of the model includes province fixed

[31] Sector s located in province p observed at time t is mafia-infiltrated if, in province p and year t, public works for the A4 highway or the high speed rail have been approved and sector s is mafia-appealing.

effects η_p and sector-year fixed effects θ_{st}. In order to control for a higher degree of unobserved heterogeneity, two additional specifications include sector-year and province-year fixed effects and sector-year, province-year and province-sector fixed effects. The three model specifications exclude the construction sector in order to avoid the bias introduced by the potential violation of the exclusion restriction assumption. In fact, the approval of renewal works for public infrastructure is likely to have an impact per se on the allocative efficiency of the construction sector.

Table A1 shows the results. Column (1) presents the results of the main specification of the model. The coefficient of mafia intensity suggests that an increase of mafia intensity correlates negatively with the allocative efficiency of mafia-appealing sectors located in the provinces where the mafia succeeded in infiltrating, after mafia arrival. Results reported in Column (2) support this idea. In Column (3), the coefficient on mafia intensity is negative, but it loses significance. This might be due to the quite limited variation brought by the high number of fixed effects.

These results suggest that the extortive behaviour of mafia groups, which increased significantly in some northern provinces because of investment in public infrastructure, negatively biased the OP covariance between productivity and size characterising the mafia-infiltrated markets. This outcome is line with the suggestive evidence presented in Section 2, where I show a decreasing trend of the OP covariance in the mafia-appealing sectors located in mafia-infiltrated provinces after the arrival of the mafia.

A.3

A brief comment on the performance of the model is worthwhile. Figure A1 provides some insights about the relationship between observed OP covariance of each mafia-infiltrated market and its simulated counterpart. The correlation between observed and simulated OP covariance is equal to 0.57. However, it can be noticed that the

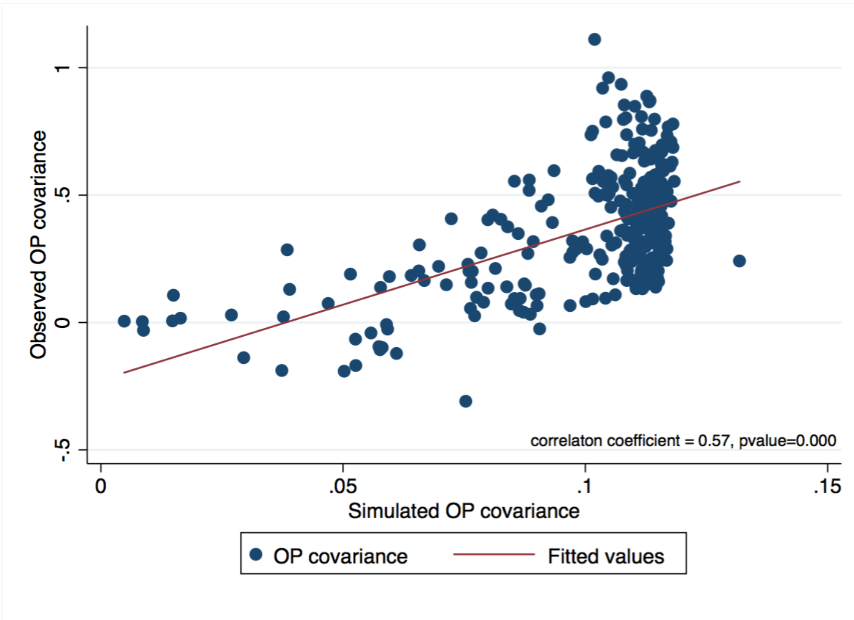
Table A1: Mafia intensity and allocative efficiency

	(1) OP covariance	(2) OP covariance	(3) OP covariance
Mafia Intensity	-0.091**	-0.099***	-0.128
	(0.036)	(0.032)	(0.231)
Observations	7,359	7,359	7,359
R-squared	0.138	0.202	0.359
Province FE	YES	NO	NO
Year FE	NO	NO	NO
Sector-Year FE	YES	YES	YES
Province-Year FE	NO	YES	YES
Province-Sector FE	NO	NO	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in columns (1)-(3) is OP covariance for log-labour productivity and share of employment computed using data from the *Small and Medium Entrepreneurs Survey* available at ADELE laboratory-ISTAT. Variable "Mafia intensity" is obtained interacting "extortion cases per 1000 firms" and "mafia-appealing sector" dummy, i.e. a dummy that takes a value of one if sector s is labelled as mafia appealing. Data on reports of extortion is provided by the Yearly Book of Criminal Statistics published by ISTAT. "Mafia intensity" is instrumented by a dummy that takes a value of one if sector s located in province p observed at time t is defined as mafia-infiltrated.

two variables have highly different scales. In particular, the simulated OP covariance is systematically lower than the observed one. This might be due to the presence in the actual data of few outliers in terms of productivity that scale up the observed OP covariance. These outliers cannot be simulated because of the distributional assumptions imposed in the model. This suspicion is corroborated by the comparison of the observed correlation between productivity and size to its simulated counterpart. The computation of the correlation coefficient requires the variance of firms' productivity at the denominator, the presence of the outliers would increase the denominator and lead to a lower correlation coefficient. Conversely, given that simulated firm-level data does not produce these outliers, the simulated correlation coefficient is not scaled down. This is what happens in the present context: the observed correlation between size and coefficient is systematically lower than the simulated one.[32]

Figure A1: OP covariance



[32]Graphs that shows the difference between observed and simulated correlation between firm productivity and size are available upon request.