

The Silent Stranglehold: Quantifying Organized Crime's Chilling Effect on Firm Efficiency and R&D

Abstract

This study examines the impact of perceived organized crime presence on firms' research and development (R&D) activities and technical efficiency. The analysis employs data derived from an original survey conducted by the Bank of Italy, encompassing a representative sample of over 2,600 Italian firms within the industrial and service sectors. The survey captures firms' perceptions regarding the presence of organized crime, which we consolidate into a synthetic measure of the perceived risk associated with mafia syndicates that may potentially impair firm operations. Our empirical findings indicate that firms operating in regions and sectors with high levels of organized crime risk are significantly more likely to experience a decline in their propensity to invest in R&D and adversely affect their technical efficiency. Organized crime appears to distort market dynamics by escalating operational costs and reducing firms' ability to utilize production factors effectively, thereby undermining entrepreneurial dynamism. These insights highlight the necessity for policymakers and financial institutions to incorporate organized crime risk into their assessment models and implement targeted financial measures to mitigate its adverse economic impacts.¹

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1. Introduction

Organized crime, particularly mafia-type syndicates, hampers firms' performance and innovation by increasing operational costs and distorting strategic decision-making. The widespread presence of criminal networks impose on firms direct costs, such as extortion, and indirect costs through heightened risk perceptions that deter productive investments or operate in corrupt environment. This uncertainty-laden environment stifles entrepreneurial dynamism, particularly in innovation-driven activities, as firms grapple with instability and insecurity. In this context, (Loncan, 2024) notes that violent crimes in Brazil are linked to a decrease in corporate investments in research and development (R&D). Similarly, Wu et al. (2025) leveraging China's 2018–2020 'Saohei Chu'e' anti-mafia campaign, found a significant reduction in patent filings in Chinese cities with a higher presence of organized crime. This view is supported by Detotto and Otranto's (2010) findings showing that criminal activity acts like a tax on the economy, discouraging investments and reducing firm competitiveness.

The economic literature highlights how organized crime distorts market efficiency by raising operational costs, leading to aggregate value-added losses

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of 0.6–8% (Piemontese, 2023).

In addition to direct costs, coercive tactics such as intimidation compel firms to adopt conservative strategies that prioritize short-term survival over long-term growth (Saridakis et al., 2015). This often results in neglecting investments in new technologies or processes that could enhance their innovative capabilities. Organized crime also enforces cartels, protecting inefficient firms and reducing market competition, which further constrains innovation (Slutzky and Zeume, 2024). Calamunci and Drago (2020) found that placing organized crime firms under judicial administration generates positive spillovers for legitimate businesses, suggesting that reducing criminal influence can alleviate financial and operational burdens, potentially fostering greater investment in innovation and efficiency.

Theoretically, criminal rent-seeking diverts resources from productive uses like innovation toward unproductive or destructive entrepreneurship (Murphy et al., 1991; Baumol, 1990).

The perceived risk of organized crime heightens uncertainty, leading firms to adopt cautious approaches and reduce spending on investment, particularly in intangible assets, which is inherently risky but essential for innovation. This is consistent with the findings of Daniele and Marani (2011), who demonstrate that organized crime negatively impacts foreign direct investment and institutional quality. Furthermore, mafia infiltration distorts markets, raises costs, and erodes institutional trust, collectively stifling innovation and growth (Fenzia and Saggio, 2024; Catino, 2020).

Globally, organized crime deters investment and growth, as seen in Eastern Europe (Krkoska and Robeck, 2006) and Mexico (de la Miyar, 2016a).

In Italy, southern provinces suffer most from mafia influence, exacerbating regional disparities and reducing innovation (Mocetti and Rizzica, 2024), including through reduced human capital formation and increased migration (Coniglio et al., 2010).

This study addresses the critical nexus between crime, risk, and investment decisions, by examining the impact of perceived organized crime on firms' R&D investments and technical efficiency, leveraging a unique dataset from the Bank of Italy's Survey on Industrial and Service Firms (INVIND, 2020), encompassing over 2,600 Italian enterprises.

In contrast to earlier research that relies on objective crime statistics (Ganau and Rodríguez-Pose, 2018), we introduce an innovative composite indicator grounded in the perception of mafia threats, developed through the Multi-Directional Benefit of the Doubt (MDBoD) methodology (Fusco, 2023). This approach effectively captures the nuanced and multifaceted nature of perceived mafia risk by overcoming the limitations of traditional aggregation techniques. Specifically, MDBoD prevents full compensability issues, where high performance in one dimension offsets deficits in others, while also accounting for the direction of performance, enabling flexible weighting of indicators based on their relative importance, and offering robustness to heterogeneous or incomplete data, making it particularly suitable for analyzing the complex dimensions of perceived mafia risk.

In the next stage of our analysis, we estimate the impact of the composite indicator of organized crime threats on firms' R&D investments. Finally, we use Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) to evaluate how this indicator affects firm production efficiency.

Our contribution is three-fold. First, we extend the literature by linking perceived criminal risk to R&D, a critical driver of innovation, thereby uncovering a novel channel through which organized crime impedes economic progress. Second, our composite indicator provides a methodological advancement by capturing the multifaceted nature of mafia influence more accurately than single-indicator approaches (e.g., [Forgione and Migliardo, 2023b](#)). Third, we offer a wake-up call for policy-targeted interventions, such as enhanced law enforcement and transparency measures, as it is necessary to remove the economic distortions caused by syndicates.

The rest of the paper is structured as follows. Section 2 surveys the literature on the economic impact of organized crime. Section 3 details the data and variables. Section 4 reports the empirical results, and Section 5 offers concluding remarks.

2. Background literature

This section surveys the literature on how organized crime distorts markets and financial systems. It examines the ways criminal networks amplify market inefficiencies, with particular attention to their effects on firms, public institutions, and credit allocation.

Organized crime and corruption significantly hinder firm performance and innovation, discouraging investment, technology adoption, and entrepreneurship ([Krkoska and Robeck, 2009](#); [Saridakis et al., 2015](#); [Anokhin and Schulze, 2009](#)). Firms in high-crime areas are 20% less likely to adopt new technologies, with both immediate and long-term effects ([Saridakis et al., 2015](#)). Effective corruption control fosters innovation ([Anokhin and Schulze, 2009](#)),

while stronger law enforcement and judicial quality boost innovation intensity in European regions (Rodríguez-Pose and Di Cataldo, 2015) and Italian provinces (Peiró-Palomino and Perugini, 2022). A negative correlation between corruption and innovation is further confirmed by Lee et al. (2020) and Dokas et al. (2023). In Italy, Barbieri and Rizzo (2023) find that higher crime rates reduce firm entry by 15%, as a result of increased risk and instability.

The widespread of criminal networks also depresses firm operation in terms of productivity (Albanese and Marinelli, 2013; Ganau and Rodríguez-Pose, 2018), revenue per employee (Buchetti et al., 2025), and technical efficiency (Forgione and Migliardo, 2023b, 2025). The proximity of the mafia disrupts economies by depleting assets, money laundering, and fostering corruption, which allows criminal enterprises to outcompete their rivals and secure public contracts (Mirenda et al., 2022). Extortion exerts a substantial financial burden on firms, particularly small and medium-sized enterprises (SMEs), as the extortion amount represents a larger proportion of their financial resources compared to larger firms (Balletta and Lavezzi, 2023). This financial strain can constrain their ability to invest in research and development (R&D) and other intangible assets.

Beyond its direct impact on firms, organized crime distorts institutional processes. Criminal groups collude with local politicians to divert public resources into sectors that are strategically vital to their illicit activities, thereby engendering an environment of heightened uncertainty and risk (Barone and Narciso, 2015; Di Cataldo and Mastrococco, 2022). In this vein, Arbolino and Boffardi (2024) show that corruption and crime undermine fund efficiency and delay cohesion policy implementation, while public ex-

penditure in high-crime regions negatively affects per capita GDP (Fioroni et al., 2025). As shown by Alam et al. (2019), corruption emerges as the single most important institutional factor shaping firms' R&D investment, while organized crime undermines market efficiency by discouraging R&D and distorting public-procurement processes (Slutzky and Zeume, 2024). By contrast, stronger local institutions help small and medium-sized enterprises become more productive (Agostino et al., 2020). Criminal infiltration of public-works procurement further warps market outcomes: Ravenda et al. (2020) report that it boosts the number of bids, increases awarded rebates, and widens execution cost overruns, while actually shortening delivery times. The cost overrun effect, however, weakens for larger projects, and installing new municipal councils after dissolutions does not materially improve contract performance. In this context, Riccardi and Maggioni (2025) identify that Italian mafia organizations strategically invest in the construction sector, particularly in regions where their territorial dominance and infiltration of public administration allow them to secure public contracts, thereby distorting market dynamics.

Evidence of anti-crime policies is increasingly encouraging. Well-targeted interventions can mitigate systemic risks and bolster medium-term competitiveness (Slutzky and Zeume, 2018; Calamunci and Drago, 2020). In Italy, Fenizia and Saggio (2024) demonstrate that dissolving city councils infiltrated by organized crime results in a 16.9% increase in employment, a 9.4% rise in the number of firms, and enhancements in business activity and property values. Similarly, Calamunci et al. (2022) find that confiscating and reallocating mafia-controlled firms increases commercial real estate prices by approxi-

mately 4%, with potential efficiency spillovers, while [Boeri et al. \(2024\)](#) report that asset confiscations negatively affect housing prices, although reallocations yield positive outcomes. Extending beyond Italy, comparable benefits have been observed in China, where anti-organized crime campaigns have elevated stock prices, particularly for firms in industries more vulnerable to organized crime, due to reduced operational risks and improved market stability ([Li and Cheng, 2024](#)). These findings suggest that curbing criminal influence enhances firm value and investor confidence, offering substantial economic advantages that highlight the value of robust anti-crime measures

Areas that are plagued by organized crime pose constant challenges for credit supply, resulting in fewer opportunities for firms to invest. Firms in high-crime regions endure higher interest rates and tighter collateral requirements ([Bonaccorsi di Patti, 2009](#); [de la Miyar, 2016b](#)). More recent research confirms that organized crime significantly reduces credit availability and increases borrowing costs for firms in Italy ([Mocetti and Rizzica, 2024](#)). Heightened risk perceptions likewise lead banks to tighten lending standards toward businesses operating in territories dominated by criminal organizations ([Bianchi et al., 2022](#)). [Buchetti et al. \(2025\)](#) illustrate that anti-mafia law enforcement activities result in an increase in bank lending to businesses within the impacted regions. However, these actions also lead to elevated borrowing costs due to heightened perceptions of risk by banks following mafia infiltration. This indicates that while the dismantling of criminal networks can enhance access to credit, the enduring influence of organized crime continues to affect the risk assessments conducted by financial institutions. Crime also shapes capital-structure choices: higher local crime

rates reduce the likelihood that firms adopt conservative financing strategies (Gama et al., 2024). Such constraints make liquidity-strapped companies prime targets for infiltration, because organized-crime syndicates can exploit their funding gaps (Arellano-Bover et al., 2024). Along similar lines, Barone and Masciandaro (2019) argue that criminal groups engage in usurious lending not only to reap exorbitant interest but also to launder illicit proceeds, either directly or indirectly.

In sum, the economics-of-crime literature shows that production outcomes, institutional quality, and wider socioeconomic conditions are highly responsive to the presence of organized-crime syndicates. Despite growing evidence on organized crime's economic toll, few studies examine its impact through the lens of perceived risk, particularly in relation to innovation and technical efficiency. While Loncan (2024) links violent crime to reduced corporate investment, our research extends this by focusing on the perceived risk of mafia-type organized crime in Italy, which may have distinct characteristics due to the structured nature of such criminal organizations. By introducing a composite indicator of perceived mafia risk, we bridge these gaps and provide a more nuanced understanding of how crime-related uncertainties affect firms' strategic decisions. Wu et al. (2025) show that China's anti-organized crime campaigns enhance long-term stock prices by improving firm innovation, further demonstrating the economic benefits of reducing criminal influence.

Against this backdrop, our study introduces a novel composite index that captures perceived criminal pressure and gauges how organized crime affects firms' R&D effort and technical efficiency.

3. Data Description and Methodology

We carry out the empirical analysis through the Bank of Italy’s Remote Execution System (REX), which runs researchers’ code on the confidential Survey on Industrial and Service Firms (INVIND, 2009–2020) covering more than 2,600 enterprises. Because of privacy safeguards, scholars cannot download the micro–data; instead, they submit scripts to REX, which executes them on secure servers. Before releasing any results, the system vets the output to ensure that no information can identify individual respondents; estimates that fail this disclosure check are withheld.

To examine how organized crime affects firms’ propensity to innovate and their technical efficiency, we draw on a set of unique items included in the 2020 wave of the INVIND survey. These questions—embedded within a wider battery—capture criminal practices commonly linked to organized networks. Using them allows for a more nuanced assessment of whether, and to what extent, exposure to such practices influences both R&D spending and efficiency.

Gathering accurate self–reported information on illicit activity is notoriously difficult. Respondents may downplay or disguise their perceptions to avoid stigma or retaliation. In particular, the rationale for measuring crime levels independently of official statistics is stronger for organized crime than for conventional crime, and population surveys are widely recognized as an effective tool for producing reliable estimates ([Van Dijk, 2007](#)). For instance, [Almeida and Montes \(2020\)](#) discuss how violence and crime negatively affect business confidence, revealing an unstable economic environment, with consequences on innovation, productivity and growth. Indeed,

the INVIND survey ensures full anonymity, which sharply reduces misreporting and social-desirability bias-concerns that loom large in studies of organized crime. The resulting confidentiality encourages frank answers and, in turn, raises the quality and representativeness of the data. Furthermore, Bank of Italy accurately choose firms to be included in the INVIND survey. In addition, the survey comprises firms with at least twenty employees, enhancing the robustness of the answers related to the spread of criminal phenomena.

The 2020 INVIND wave is particularly relevant because asked each respondent to gauge how likely it is that a business owner in the same geographical area and economic sector had (i) obtained credit through unofficial channels (e.g., at usurious rates); (ii) received an offer to sell the firm under irregular terms (abnormal prices or payment schedules); or (iii) been threatened, intimidated, or extorted. Answers were recorded on a four-point Likert scale-“not at all likely”, “unlikely”, “somewhat likely”, and “very likely”. We treat these items as signals of mafia-type organized crime, because the repeated or joint occurrence of such episodes points to coordinated criminal activity rather than isolated offenses. To capture their combined intensity, we aggregate the three items into a composite index-a standard way to compress several indicators into a single metric when studying complex, intangible phenomena like organized-crime pressure.

To integrate the perceived presence of organized crime across multiple dimensions into a single composite index (*Organized crime risk_{CI}*), we employ the Multi-Directional Benefit of the Doubt (MDBoD) methodology (Fusco, 2023), which refines and extends the standard Benefit of the Doubt (BoD)

approach (Cherchye et al., 2007). Before estimating this composite indicator, we normalize the individual indicators of organized crime perception to ensure comparability across dimensions. Specifically, we implement the min–max normalization technique, defined as follows:

$$\tilde{I}_k = \frac{I_k - \min(I_k)}{\max(I_k) - \min(I_k)}, \quad k = 1, \dots, K. \quad (1)$$

This normalization procedure ensures comparability across indicators by rescaling them to the $[0, 1]$ interval. Subsequently, we apply the MDBoD approach to aggregate these normalized indicators into a composite measure. This method not only generates an integrated index but also illuminates specific inefficiencies within individual components, thereby offering actionable insights for targeted policy interventions and enhancing the overall utility and relevance of the resulting indicator.

The MDBoD method is grounded in the Data Envelopment Analysis (DEA) framework introduced by Charnes et al. (1978), a non–parametric technique widely used to estimate the relative efficiency of decision–making units (DMUs). In this setting, DEA benchmarks each DMU’s performance against a constructed frontier of “best practices”. The MDBoD model is an advanced extension of conventional BoD techniques, developed to mitigate the influence of outliers and anomalies, enhance the robustness of efficiency assessments, and provide tailored improvement strategies for each DMU. Building upon the principles of Multi–directional Efficiency Analysis (MEA), MDBoD employs an iterative sampling process that compares each DMU against subsets of size m , smaller than the total number of observations N . This procedure facilitates the estimation of a robust frontier and determines the maximum potential improvement for each indicator. Addi-

tionally, MDBoD avoids implicit compensability among individual indicators and supplies performance benchmarks for every DMU.

The first step in implementing the MDBoD methodology is to determine the optimal value $\tilde{y}_{j,k}$ for each indicator k of a DMU j , while holding the other indicators constant. This objective is achieved by solving the following optimization problem:

$$\max_{\tilde{y}_{j,k}, \alpha_1, \dots, \alpha_N} \tilde{y}_{j,k} \quad \text{subject to} \quad \begin{cases} \tilde{y}_{j,k} \leq \sum_{i=1}^N \alpha_i y_{i,k}, & \forall k, \\ y_{j,h} \leq \sum_{i=1}^N \alpha_i y_{i,h}, & \forall h \neq k, \\ \alpha_i \geq 0, & \forall i, \end{cases}$$

where $y_{i,k}$ denotes the observed value of indicator k for DMU i , α_i represents the non-negative weights assigned to each reference DMU, and N is the total number of DMUs.

For each DMU j , the directional vector is defined by the difference between its ideal $\tilde{y}_{j,k}$ and its observed value $y_{j,k}$ for each indicator k :

$$\mathbf{d}_j = (\tilde{y}_{j,1} - y_{j,1}, \tilde{y}_{j,2} - y_{j,2}, \dots, \tilde{y}_{j,K} - y_{j,K}),$$

where K denotes the total number of individual indicators. This vector defines the specific improvement direction for DMU j .

For each DMU j , the benchmark is obtained by solving a maximization problem that determines the proportion β_j required to reach the efficiency frontier along the directional vector \mathbf{d}_j . The optimization problem is formulated as follows:

$$\max_{\beta, \alpha_1, \dots, \alpha_N} \beta \quad \text{subject to} \quad \begin{cases} y_{j,k} + \beta d_{j,k} \leq \sum_{i=1}^N \alpha_i y_{i,k}, & \forall k, \\ \alpha_i \geq 0, & \forall i, \end{cases}$$

where β represents the proportion of improvement necessary to reach the benchmark, $d_{j,k} = \tilde{y}_{j,k} - y_{j,k}$ is the directional component for indicator k , and $\sum_{i=1}^N \alpha_i y_{i,k}$ is the linear combination of efficient DMUs (the efficiency frontier).

Finally, the measure is calculated as follows:

$$B_j = y_j + \beta^* \mathbf{d}_j,$$

where β^* is the optimal solution to the maximization problem.

The efficiency for each indicator k of DMU j is calculated as follows:

$$E_{j,k} = \frac{y_{j,k}}{y_{j,k} + \beta^* d_{j,k}}$$

This value indicates how much improvement is needed for indicator k for DMU j to meet the benchmark.

Finally, the composite indicator for DMU j is calculated as follows:

$$CI_j = 1 - \frac{\beta^* \sum_{k=1}^K d_{j,k}}{\sum_{k=1}^K (y_{j,k} + \beta^* d_{j,k})}$$

This composite score integrates the three organized crime perception indicators from the INVIND dataset. To assess the impact of the *Organized crime risk_{CI}* on firms' R&D investment, we employ an instrumental variable approach and perform a two stage least squares analysis, specified as follows:

$$\text{Organized crime risk}_{CIi} = a_0 + a_1 \text{Instrument}_i + a_2 Z_i + u_i \quad (2)$$

$$\ln R\&D = a_0 + a_1 \text{Predicted}(\text{Organized crime risk}_{CI})_i + a_2 Z_i + u_i \quad (3)$$

where R&D represents the current R&D expenditure, while *Instrument* represents the vector of the instrumental variables employed in the study (i.e.,

Geo Area, *Legal Status* and *Operating Result*). Z includes the control variables employed also in the estimation of technical efficiency. These variables include *Size*, a categorical measure denoting the number of employees, and *Age*, reflecting the number of years the firm has been in operation. *Export* is a multinomial variable, distinguishing categories of export share as a percentage of total turnover. *Macro sector* is a categorical indicator identifying the industry in which the enterprise operates. *Competition* is a dummy variable which captures if the firm's price development is mainly influenced by competitors' pricing policies.

To assess the impact of *Organized crime risk_{CI}* on firm efficiency, we employ both SFA and DEA. SFA is a parametric technique premised on the assumption that no economic agent can exceed the ideal efficiency frontier, with any deviations signifying individual inefficiencies (Belotti et al., 2013).

Specifically, the output of the cross-sectional SFA is given as follows:

$$y_i = \alpha + \mathbf{x}'_i \beta + \nu_i - v_i \quad (4)$$

where α is the constant term, \mathbf{x}' is the vector of explanatory variables, and β represents the associated parameters. The error term comprises two components: the common white noise term (ν_i), assumed to be normally distributed with zero mean and homoskedastic variance, and the inefficiency term v_i which captures deviations from the maximum achievable output for given inputs. The inefficiency term v_i is constrained to follow a half-normal distribution (i.e., a normal-half-normal distribution). The normalized stochastic production function is specified in a translog form as follows:

$$\ln Q_i = \beta_0 + \sum_{j=1}^3 \beta_j \ln X_{ij} + \frac{1}{2} \sum_{j=1}^3 \sum_{k=1}^3 \beta_{jk} \ln X_{ij} \ln X_{ik} + (\nu_i - v_i) \quad (5)$$

where Q denotes the output proxied by the turnover. R , L and K represent the three inputs: production cost, total staff expense and capital stock, respectively. Due to privacy restrictions, the dataset does not include direct observations of capital stock. Consequently, and following [Forgione and Migliardo \(2023a\)](#), we estimate capital stock using the perpetual inventory method described in ([Berlemann and Wesselhöft, 2014](#)):

$$\begin{aligned}
k_{\alpha,t} &= \sum_{i=0}^{\infty} (1 - \delta_{\alpha})^i I_{\alpha,t-(i+1)} & k_{\beta,t} &= \sum_{i=0}^{\infty} (1 - \delta_{\beta})^i I_{\beta,t-(i+1)} \\
k_{\gamma,t} &= \sum_{i=0}^{\infty} (1 - \delta_{\gamma})^i I_{\gamma,t-(i+1)} & k_{\xi,t} &= \sum_{i=0}^{\infty} (1 - \delta_{\xi})^i I_{\xi,t-(i+1)} \\
k_{\eta,t} &= \sum_{i=0}^{\infty} (1 - \delta_{\eta})^i I_{\eta,t-(i+1)}
\end{aligned}$$

where α represents a company's investment in buildings, β in plants, machinery, and equipment, γ in means of transport, ξ in software and databases, and η in research and development. The applied depreciation rates align with the relevant fiscal coefficients. Finally, k_i denotes the cumulative value of both tangible and intangible asset investments over time, appropriately weighted by the respective depreciation rates. The sum of these sub-capital stocks constitutes the total capital stock (K) for firm i , which is then employed in the SFA.

The production frontier and the coefficients of the inefficiency determinants are estimated simultaneously by applying the one-step approach, thereby avoiding the bias associated with the alternative two-stage method ([Schmidt, 2011](#)). The inefficiency equation is specified as follows:

$$\sigma_{vi}^2 = \exp(\delta_v, z_{vi}) \tag{6}$$

where δ denotes a vector of parameters to be estimated, while z_{vi} is a vector of environmental variables influencing firms' inefficiency. These variables include *Organized crime risk_{CI}* and the set of control variables already employed in the R&D analysis, as specified below:

$$z_i = [\textit{Organized crime risk}_{CIi}, \textit{Size}_i, \textit{Age}_i, \textit{Export}_i, \\ \textit{Macro sector}_i, \textit{Competition}_i] \quad (7)$$

Moreover, we reinforce our study by implementing the Algorithm 2 from [Simar and Wilson \(2007\)](#). In the first stage, a nonparametric DEA frontier approach is used to obtain technical (in)efficiency scores, which are then regressed against a set of covariates in the second stage². In contrast to SFA, DEA employs mathematical programming to evaluate efficiency across multiple DMUs. In our case, the approach is output-oriented, aiming to expand the output vector without modifying inputs, provided that production remains within the feasible frontier. For this study, we estimate a DEA-CCR model, under the assumption of Constant Returns to Scale (CRS) ([Charnes et al., 1978](#)). Similar to the MDBoD approach, this model is expressed through the following linear programming problem:

$$\max_{\phi, \lambda_j} \phi \quad \text{subject to} \quad \begin{cases} \sum_{j=1}^n \lambda_j x_{i,j} \leq x_{i,0}, & i = 1, \dots, m, \\ \sum_{j=1}^n \lambda_j y_{r,j} \geq \phi y_{r,0}, & r = 1, \dots, s, \\ \lambda_j \geq 0, & j = 1, \dots, n. \end{cases}$$

²We set L₁=100 replications in the first loop to compute bias-corrected efficiency estimates and L₂=2000 replications is the second loop to bootstrap the truncated regression model.

where x_{ij} and y_{ij} denote the i -th input and r -th output of DMU j . The parameter $\phi \geq 1$ reflects the proportional expansion of DMU₀'s outputs without exceeding its current input levels. A value of $\phi^* = 1$ indicates that the DMU is on the efficiency frontier, while $\phi^* > 1$ implies potential for further output increases. Under the CRS assumption, the λ_j terms form a convex combination of DMUs serving as a reference benchmark. The output, inputs and environmental variables employed in the second-stage analysis are identical to those specified for the SFA.

Table 1 provides the definitions of all variables used in this study, while Table 2 presents the corresponding summary statistics.

The sample comprises a diverse array of Italian firms from both industrial and service sectors across the country. The descriptive statistics shed light on the attributes of the firms in our sample and highlight the obstacles they face in the context of organized crime.

The variable measuring perceived organized crime risk (*Organized crime risk_{CI}*) reveals nuanced differences in firms' perceptions of criminal threats. On average, the composite indicator suggests that these threats are generally viewed as relatively unlikely. However, the standard deviation indicates substantial heterogeneity, with some firms perceiving the risks as moderate or high. This variation underscores the dual benefit of the composite indicator: it consolidates multiple dimensions of criminal risk into a single measure while preserving the granularity needed to identify firms facing elevated exposure.

The control variables exhibit substantial heterogeneity across the sample, reflecting the diverse profiles of firms operating in varied economic and institutional contexts. For instance, firm size and age range widely—from small,

Table 1: Variables description.

Variable name	Variable	Description
Output Q	Continuous	Firm's turnover, winsorized at 5%
Input R	Continuous	Firm's production cost, winsorized at 5%
Input L	Continuous	Firm's total staff expense, winsorized at 5%
Input K	Continuous	Firm's capital stock, winsorized at 5%
Organized crime risk _{CI}	Continuous	Estimated composite indicator
R&D	Continuous	Expenditure on R&D, winsorized at 5%
Size ¹	Multinomial	Six categories
Age	Continuous	Firm's age, winsorized at 5%
Macro sector	Multinomial	
		Manufacturing
		Energy extraction
		Non-financial private services
Export share	Multinomial	
		Non-exporting firms
		Firm exporting less than 1/3 of their turnover
		Firm exporting between 1/3 and 2/3 of their turnover
		Firm exporting more than 2/3 of their turnover
Competition	Dummy	Price setting depending mainly on competitors
Firm Geo Area	Multinomial	
		Northwest
		Firm headquarter in the Northwest of Italy
		Northeast
		Firm headquarter in the Northeast of Italy
		Centre
		Firm headquarter in the Centre of Italy
		South and islands
		Firm headquarter in the South and islands of Italy
Legal status	Multinomial	
		Limited Liability Company (<i>LLC</i>)
		Public Limited Company (<i>PLC</i>)
		Partnership Limited by Shares (<i>PLS</i>)
		Cooperative (<i>Coop</i>)
		Limited Partnership (<i>LP</i>)
		General Partnership (<i>GP</i>)
		Other
Operating result	Multinomial	Five categories
		Large profit
		Small profit
		Broad balance
		Small loss
		Large loss

¹0=20-49; 1=50-99; 2=100-199; 3=200-499; 4=500-999; 5=1000 workers or more.

Table 2: Summary statistics.

Variable	Num. Obs.	Mean	Std. Dev.	Min	Max
Output Q	2,180	63,473.082	101,653.150
Input R	2,180	43,552.705	73,673.15
Input L	2,180	7,265.614	11,308.550
Input K	2,180	10,063.604	18,040.59
Organized crime risk _{CI}	2,631	0.148	0.212	0	1
R&D	2,631	153.210	371.941
Size	2,631	1.538	1.466	0	5
Age	2,631	38.272	20.188
Macro sector	2,631	1.642	0.915	1	3
Export share	2,631	1.207	1.077	0	3
Competition	2,631	0.125	0.331	0	1
Geo Area	2,631	2.697	1.131	1	4
Legal status	2,631	1.726	0.954	1	7
Operating result	2,631	2.463	1.222	1	5

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Missing values due to privacy constraints.

nascent enterprises to large, well-established corporations—highlighting a dichotomy that is critical for understanding differences in efficiency. Differences in sectoral composition and export orientation ensure that the sample encompasses firms with varied exposure to market volatility and international competition. This diversity underscores the importance of including these control variables to isolate the relationships among organized crime risks, firms’ R&D expenditure, and technical efficiency. Moreover, the observed heterogeneity aligns with theoretical frameworks suggesting that firm-specific and contextual factors dynamically interact to shape financing outcomes.

4. Empirical Results

This section presents the empirical findings regarding the determinants of firms’ aptitude to innovate and technical efficiency, as measured by both SFA and DEA, as well as the determinants of the *Organized crime risk_{CI}*.

The estimation of the impact of organized crime perception on R&D is conducted through the instrumental variable estimator, to avoid possible endogeneity problems. In particular, *Geo Area*, *Legal Status* and *Operating Result* are employed as instruments for the potential endogenous variable *Organized crime risk_{CI}*.

The empirical findings reported in Table 3 show that a higher *Organized crime risk_{CI}* leads to a reduction of firms’ expenditure in research and development with a coefficient significant at 5% level. On the other hand, larger firms appear to be more proactive to invest in R&D, as the exporting firms. For what regards the *Macro Sector*, *Energy extraction* and *Non-financial private services* show a lower propensity to R&D than their manufacturing

counterparts. The robustness of the model is provided by the diagnostics tests: the *Wu-Hausman* test provide evidence about the presence of endogeneity in the simple linear model, requiring the instrumental variable approach, while the *Weak instruments* and the *Sargan* tests validate the choice of the instruments because they are not weak and they are exogenous.

Table 4 presents the estimation results of the determinants of technical inefficiency, as obtained through SFA. The statistically significant coefficients from our frontier estimates indicate that the translog function is better suited to capture the sample’s heterogeneity. Since our analysis covers firms from various sectors—with different production methods, input usage, technologies, and operational traits—the translog model provides a more detailed representation than the Cobb–Douglas production function. Moreover, its flexibility in accommodating varying substitution elasticities and nonlinear effects further emphasizes its advantage, particularly when modeling the interactions among production factors in such a diverse sample. The results related to the efficiency determinants indicate that the coefficient associated with *Organized crime risk_{CI}* is statistically significant at the 1% level, suggesting that higher perceptions of organized crime are associated with increased technical inefficiency. Most control variables are statistically significant. In particular, firms employing more workers exhibit lower efficiency (i.e., higher technical inefficiency). With respect to the *Export share*, exporting firms tend to demonstrate improved efficiency, which corresponds to a reduction in technical inefficiency at 10%. Additionally, firms operating in the non–financial private services sector experience higher technical inefficiency compared to their manufacturing counterparts. Finally, the coefficient for older enter-

Table 3: Instrumental variable estimates.

	(I)	(II)
<i>Dependent variable</i>	<i>Organized crime risk_{CI}</i>	<i>ln R&D</i>
<i>Organized crime risk_{CI}</i>		-5.655** (2.539)
<i>Size</i>		0.257*** (0.038)
<i>Export share</i>		0.525*** (0.058)
<i>Competition</i>		0.237(0.165)
<i>Manufacturing</i>		Benchmark
<i>Energy extraction</i>		-0.733** (0.303)
<i>Non – financial private services</i>		-0.916*** (0.141)
<i>Age</i>		0.002(0.003)
<i>Intercept</i>	-0.017(0.069)	1.743*** (0.366)
<i>Northwest</i>	Benchmark	
<i>Northeast</i>	0.012(0.013)	
<i>Centre</i>	0.005(0.012)	
<i>South and islands</i>	0.029** (0.013)	
<i>LP</i>	Benchmark	
<i>LLC</i>	0.098(0.067)	
<i>PLC</i>	0.088(0.067)	
<i>Coop</i>	0.121* (0.070)	
<i>GP</i>	0.084(0.090)	
<i>Other</i>	0.104(0.078)	
<i>Operating result</i>	0.013*** (0.003)	
<i>Diagnostics tests</i>		
<i>Weak instruments test</i>	2.868*** (0.002)	
<i>Wu – Hausman test</i>	6.912*** (0.009)	
<i>Sargan test</i>	11.674(0.166)	

Number of observations: 2,631. Standard errors are reported in parentheses, *p<0.10, **p<0.05, ***p<0.01. (I) denotes the first stage, where *Geo Area*, *Legal Status* and *Operating Result* were employed as instruments. For diagnostics tests, results are presented while values in italics reported in parentheses are p-values.

prises is significant at the 5% level and indicates a reduction in technical inefficiency.

Table 5 presents the determinants of technical inefficiency, as estimated using DEA. Consistent with the one-step SFA results, the *Organized crime risk_{CI}* variable is associated with reduced technical efficiency. The corresponding confidence intervals corroborate that this effect is significant at the 5% level. Moreover, a higher number of workers is linked to a decline in technical efficiency, with confirmed advantages related the exporting firms. Finally, the variables *Macro sector* and *Competition* do not exhibit statistically significant effects, while the *Age* variable is significant also in this case in reducing technical inefficiency.

These results show the detrimental effects of organized crime on firms' activity. In particular, the statistically significant effect on the R&D expenditure represents a huge problem for companies' innovation aptitude. This effect consequently influence firms' choices and thei resources implementation. In this vein, indeed, both the SFA and DEA models provide empirical evidence that *Organized crime risk_{CI}* has a significant and negative effect on firm efficiency. These findings suggest that firms operating in environments characterized by a heightened risk of organized crime tend to exhibit lower levels of efficiency.

5. Concluding remarks

Although the economic costs of organized crime are well documented, much less is known about its knock-on effects on firms' willingness to innovate. This study fills that gap by showing how Italian firms' perceptions

Table 4: Translog model estimates.

	$\ln[Q_i]$
$\ln[R_i]$	0.713*** (0.010)
$\ln[L_i]$	0.290*** (0.014)
$\ln[K_i]$	0.034*** (0.008)
$1/2(\ln[R_i] \times \ln[L_i])$	-0.429*** (0.016)
$1/2(\ln[R_i] \times \ln[K_i])$	-0.023*** (0.006)
$1/2(\ln[L_i] \times \ln[K_i])$	0.020** (0.010)
$1/2(\ln[R_i])^2$	0.238*** (0.008)
$1/2(\ln[L_i])^2$	0.226*** (0.017)
$1/2(\ln[K_i])^2$	0.005* (0.003)
Intercept	11.142*** (0.027)
σ_v	
<i>Organized crime risk_{CI}</i>	2.503*** (0.861)
<i>Size</i>	0.395** (0.164)
<i>Export share</i>	-0.361* (0.186)
<i>Competition</i>	-0.964 (0.758)
<i>Manufacturing</i>	Benchmark
<i>Energy extraction</i>	-0.523 (1.092)
<i>Non – financial private services</i>	1.403*** (0.523)
<i>Age</i>	-0.018** (0.007)
<i>Intercept</i>	-5.056*** (1.213)
σ_v	-2.432*** (0.041)

Number of observations: 2,180. Standard errors are reported in parentheses, *p<0.10, **p<0.05, ***p<0.01.

Table 5: Data Envelopment Analysis estimates.

	<i>Technical inefficiency</i>
<i>Organized crime risk_{CI}</i>	1.425(0.172; 2.758)
<i>Size</i>	0.439(0.256; 0.623)
<i>Export share</i>	-0.350(-0.655; -0.042)
<i>Competition</i>	-0.196(-1.053; 0.674)
<i>Manufacturing</i>	Benchmark
<i>Energy extraction</i>	-0.719(-2.235; 1.020)
<i>Non – financial private services</i>	-0.230(-0.927; 0.463)
<i>Age</i>	-0.016(-0.030; -0.001)
<i>Intercept</i>	6.257(5.406; 7.155)

Number of observations: 2,180. Confidence intervals at 95% level are reported in parentheses.

of organized–crime pressure shape both R&D investment and technical efficiency. Using the 2020 wave of the Bank of Italy’s INVIND survey, we find that illicit practices linked to criminal networks foster a hostile business climate, discourage entrepreneurship, and, in turn, significantly erode firm–level efficiency.

A key contribution of this study is the construction of a composite indicator that condenses several facets of perceived organized-crime risk by means of the MDBoD methodology (Fusco, 2023). The resulting index offers a robust, system–wide gauge of criminal pressure. Empirically, it emerges as a statistically significant driver for firms to cut R&D spending, indicating that criminal influence hampers innovation. In this way, We uncovered a novel channel which links the perceived organized crime presence with innovativeness. As a consequence, firms located in areas with higher perception scores display lower technical efficiency in both Stochastic Frontier Analysis

and Data Envelopment Analysis specifications. This regressive effect amplifies existing vulnerabilities, triggering a feedback loop in which exposure to organized crime further constrains a firm’s ability to deploy its production factors effectively.

These findings reinforce and broaden the evidence provided by [Forgione and Migliardo \(2023b\)](#) and [Forgione and Migliardo \(2025\)](#), who link organized crime to deteriorating technical efficiency. We show that criminal infiltration further drags down firm performance, raising operating costs for businesses forced to navigate mafia-type pressures. Beyond efficiency,

Our results point to the need for proactive, multifaceted policies that blunt the economic damage wrought by organized crime. Targeted interventions—such as bolstering law-enforcement capacity, streamlining judicial procedures, and strengthening whistle-blower protections—can reduce both the perceived and the actual risks faced by firms in high-crime areas.

Although this study yields important insights, it has several limitations. Most notably, our indicator of organized-crime pressure rests on firms’ subjective risk perceptions, which may embed reporting biases. Yet perception-based data capture on-the-ground realities—including episodes that never surface in official records because of fear of retaliation—and therefore may track operational conditions more closely than lagged judicial statistics. Future work could triangulate these perceptions with objective indicators such as police reports, court rulings, or anti-mafia enforcement actions to deliver a fuller picture of criminal infiltration and its economic fallout.

Italy is an ideal laboratory for studying how organized crime shapes business efficiency, yet it is unclear whether our findings travel beyond its borders.

Cross-national comparisons could test whether differences in legal regimes, enforcement capacity, and cultural norms modulate the economic toll of criminal networks. Although we control for a broad set of firm-level and regional covariates, unobserved factors—such as local governance quality or the scope of anti-crime initiatives—may still bias the estimates. Future research that adopts longitudinal or quasi-experimental designs could trace how policy shifts or exogenous shocks alter the relationship between organized crime and corporate performance.

In conclusion, we show that organized-crime syndicates indirectly stifle regional development by dampening innovation and draining firms' technical efficiency. Fighting organized crime is therefore not merely a policing matter but a core economic priority—one that is indispensable for restoring an environment conducive to investment, technological progress, and sustainable growth.

References

- Agostino, M., Di Tommaso, M.R., Nifo, A., Rubini, L., Trivieri, F., 2020. Institutional quality and firms' productivity in european regions. *Regional Studies* 54, 1275–1288.
- Alam, A., Uddin, M., Yazdifar, H., 2019. Institutional determinants of r&d investment: Evidence from emerging markets. *Technological Forecasting and Social Change* 138, 34–44.
- Albanese, G., Marinelli, G., 2013. Organized crime and productivity: Evidence from firm-level data. *Rivista italiana degli economisti* 18, 367–394.

- Almeida, A.F.G., Montes, G.C., 2020. Effects of crime and violence on business confidence: evidence from rio de janeiro. *Journal of Economic Studies* 47, 1669–1688.
- Anokhin, S., Schulze, W.S., 2009. Entrepreneurship, innovation, and corruption. *Journal of business venturing* 24, 465–476.
- Arbolino, R., Boffardi, R., 2024. Organized crime and corruption: what are the consequences for italian cohesion policy investments? *Regional Studies* 58, 178–193.
- Arellano-Bover, J., De Simoni, M., Guiso, L., Macchiavello, R., Marchetti, D.J., Prem, M., 2024. *Mafias and firms* .
- Balletta, L., Lavezzi, A.M., 2023. The economics of extortion: Theory and the case of the sicilian mafia. *Journal of Comparative Economics* 51, 1109–1141.
- Barbieri, N., Rizzo, U., 2023. The impact of crime on firm entry. *Journal of Regional Science* 63, 446–469.
- Barone, G., Narciso, G., 2015. Organized crime and business subsidies: Where does the money go? *Journal of Urban Economics* 86, 98–110.
- Barone, R., Masciandaro, D., 2019. Cryptocurrency or usury? crime and alternative money laundering techniques. *European Journal of Law and Economics* 47, 233–254.
- Baumol, W.J., 1990. Entrepreneurship: Productive, unproductive, and destructive. *Journal of Political Economy* 98, 893–921. doi:[10.1086/261712](https://doi.org/10.1086/261712).

- Belotti, F., Daidone, S., Ilardi, G., Atella, V., 2013. Stochastic frontier analysis using stata. *The Stata Journal* 13, 719–758.
- Berlemann, M., Wesselhöft, J.E., 2014. Estimating aggregate capital stocks using the perpetual inventory method: A survey of previous implementations and new empirical evidence for 103 countries. *Review of Economics* 65, 1–34.
- Bianchi, P.A., Marra, A., Masciandaro, D., Pecchiari, N., 2022. Organized crime and firms’ financial statements: Evidence from criminal investigations in italy. *The Accounting Review* 97, 77–106.
- Boeri, F., Di Cataldo, M., Pietrostefani, E., 2024. Localized effects of confiscated and re-allocated real estate mafia assets. *Journal of Economic Geography* 24, 219–240.
- Buchetti, B., Fabrizi, M., Ipino, E., Miquel-Flores, I., Parbonetti, A., 2025. Organized crime and banks: assessing the effects of anti-mafia police actions on lending .
- Calamunci, F., Drago, F., 2020. The economic impact of organized crime infiltration in the legal economy: Evidence from the judicial administration of organized crime firms. *Italian Economic Journal* 6, 275–297.
- Calamunci, F.M., Ferrante, L., Scebba, R., 2022. Closed for mafia: Evidence from the removal of mafia firms on commercial property values. *Journal of Regional Science* 62, 1487–1511.
- Catino, M., 2020. Italian organized crime since 1950. *Crime and Justice* 49, 69–140.

- Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. *European journal of operational research* 2, 429–444.
- Cherchye, L., Moesen, W., Rogge, N., Puyenbroeck, T.V., 2007. An introduction to ‘benefit of the doubt’ composite indicators. *Social indicators research* 82, 111–145.
- Coniglio, N.D., Celi, G., Scagliusi, C., et al., 2010. Organized crime, migration and human capital formation: Evidence from the south of italy. *Southern Europe Research in Economic Studies* .
- Daniele, V., Marani, U., 2011. Organized crime, the quality of local institutions and fdi in italy: A panel data analysis. *European Journal of Political Economy* 27, 132–142.
- Detotto, C., Otranto, E., 2010. Does crime affect economic growth? *Kyklos* 63, 330–345.
- Di Cataldo, M., Mastrorocco, N., 2022. Organized crime, captured politicians, and the allocation of public resources. *The Journal of Law, Economics, and Organization* 38, 774–839.
- Dokas, I., Panagiotidis, M., Papadamou, S., Spyromitros, E., 2023. Does innovation affect the impact of corruption on economic growth? international evidence. *Economic Analysis and Policy* 77, 1030–1054.
- Fenzia, A., Saggio, R., 2024. Organized crime and economic growth: Evidence from municipalities infiltrated by the mafia. Technical Report. National Bureau of Economic Research.

- Fioroni, T., Lavezzi, A.M., Trovato, G., 2025. Organized crime, corruption, and economic growth. *Journal of Regional Science* 65, 535–560.
- Forgione, A.F., Migliardo, C., 2023a. Disrupting regional efficiency gaps via industry 4.0 firm investments. *Industry and Innovation* 30, 135–158.
- Forgione, A.F., Migliardo, C., 2023b. Mafia risk perception: Evaluating the effect of organized crime on firm technical efficiency and investment proclivity. *Socio-Economic Planning Sciences* 88, 101619.
- Forgione, A.F., Migliardo, C., 2025. The mafia’s economic grip: Firm efficiency and a composite indicator of organized crime. *Journal of Regional Science* n/a.
- Fusco, E., 2023. Potential improvements approach in composite indicators construction: The multi-directional benefit of the doubt model. *Socio-Economic Planning Sciences* 85, 101447.
- Gama, P.M., Sol Murta, F., Vieira, E.S., 2024. Local banking development and sme conservative financing policy. does bank branch density matter? *Small Business Economics* , 1–19.
- Ganau, R., Rodríguez-Pose, A., 2018. Industrial clusters, organized crime, and productivity growth in italian smes. *Journal of Regional Science* 58, 363–385.
- Krkoska, L., Robeck, K., 2006. The impact of crime on the enterprise sector: Transition versus non-transition countries. Technical Report.

- Krkoska, L., Robeck, K., 2009. Crime, business conduct and investment decisions: Enterprise survey evidence from 34 countries in europe and asia. *Review of Law & Economics* 5, 493–516.
- Lee, C.C., Wang, C.W., Ho, S.J., 2020. Country governance, corruption, and the likelihood of firms' innovation. *Economic Modelling* 92, 326–338.
- Li, Z., Cheng, M., 2024. The impacts of anti-organized crime on asset prices: Evidence from china. *Economic Systems* 48, 101198.
- Loncan, T., 2024. Killing growth: Homicides and corporate investment in brazil. *The Journal of Development Studies* 60, 533–552.
- Mirenda, L., Mocetti, S., Rizzica, L., 2022. The economic effects of mafia: Firm level evidence. *American Economic Review* 112, 2748–2773.
- de la Miyar, J.R.B., 2016a. The economic consequences of the mexican drug war. *Peace Economics, Peace Science and Public Policy* 22, 213–246. doi:[10.1515/peps-2016-0003](https://doi.org/10.1515/peps-2016-0003).
- de la Miyar, J.R.B., 2016b. The economic consequences of the mexican drug war. *Peace Economics, Peace Science and Public Policy* 22, 213–246.
- Mocetti, S., Rizzica, L., 2024. Organized crime in italy: An economic analysis. *Italian Economic Journal* 10, 1339–1360.
- Murphy, K.M., Shleifer, A., Vishny, R.W., 1991. The allocation of talent: Implications for growth. *The RAND Journal of Economics* 22, 160–174. doi:[10.2307/2601008](https://doi.org/10.2307/2601008).

- Bonaccorsi di Patti, E., 2009. Weak institutions and credit availability: the impact of crime on bank loans. *Bank of Italy Occasional Paper* .
- Peiró-Palomino, J., Perugini, F., 2022. Regional innovation disparities in italy: The role of governance. *Economic Systems* 46, 101009.
- Piemontese, L., 2023. Uncovering illegal and underground economies: The case of mafia extortion racketeering. *Journal of Public Economics* 227, 104997.
- Ravenda, D., Giuranno, M.G., Valencia-Silva, M.M., Argiles-Bosch, J.M., García-Blandón, J., 2020. The effects of mafia infiltration on public procurement performance. *European Journal of Political Economy* 64, 101923.
- Riccardi, M., Maggioni, M.A., 2025. Bricks or cooks? geographical and social determinants of the investment choices of mafia-type organized crime. *Criminology & Criminal Justice* 25, 171–199.
- Rodríguez-Pose, A., Di Cataldo, M., 2015. Quality of government and innovative performance in the regions of europe. *Journal of economic geography* 15, 673–706.
- Saridakis, G., Mohammed, A.M., Sookram, S., 2015. Does crime affect firm innovation? evidence from trinidad and tobago. *Economics Bulletin* 35, 1205–1215.
- Schmidt, P., 2011. One-step and two-step estimation in sfa models. *Journal of Productivity analysis* 36, 201–203.

- Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of econometrics* 136, 31–64.
- Slutzky, P., Zeume, S., 2018. Organized crime and firms: Evidence from italy. Available at SSRN .
- Slutzky, P., Zeume, S., 2024. Organized crime and firms: Evidence from antimafia enforcement actions. *Management Science* 70, 6569–6596.
- Van Dijk, J., 2007. Mafia markers: assessing organized crime and its impact upon societies. *Trends in organized crime* 10, 39–56.
- Wu, W., Lan, H., Ma, Y., Lin, X., 2025. The dark hand of the underworld: measuring the economic impact of organized crime. *Crime, Law and Social Change* 83, 1–26.