BCrime and Credit: Analyzing the Impact of Organized Crime Perceptions on Loan Restrictions

Abstract

This study investigates the influence of organized crime on the restriction of credit in Italy. It utilizes a distinctive dataset obtained from a survey carried out by the Bank of Italy, which includes approximately 3000 companies in the industrial and service sectors. The study examines the extent to which the perception of organized crime affects banks' choices to limit credit availability. The results indicate that companies located in regions with a higher perception of organized crime encounter substantial difficulties in obtaining loans, suggesting a clear correlation between the presence of organized crime and heightened credit restrictions. This relationship remains strong and consistent across different specifications of credit rationing and models of firm performance. The analysis also examines the wider economic ramifications of these dynamics, highlighting that organized crime not only hampers firms' credit accessibility but also incurs broader societal expenses, impeding economic growth and development. It is recommended that policymakers take into account the complex relationships between organized crime and financial accessibility, as addressing these effects can result in enhanced firm performance and overall economic welfare. This contribution is crucial for comprehending the diverse impacts of organized crime on the economy and emphasizes the significance of tackling these challenges to promote de-

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velopment.

Keywords: Organized Crime, Credit Rationing, Technical Efficiency, Stochastic Frontier Analysis

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1. Introduction

The presence of criminal groups poses a constant challenge to institutions and society, and Italy serves as a case study for a country dealing with complex network issues related to organized crime. In fact, illegal activities carried out by mafias have a significant impact on the heterogeneity of economic development, public safety, and social development in certain parts of the Italian regions. In this wave, Pinotti (2015) provides one of the first tangible evidence about the economic costs of organized crime, demonstrating that its presence led to a loss of 16% in GDP *per capita* in southern Italy. Criminal organizations act as market barriers, fostering a less innovative environment and impeding the competitive bidding process for government procurement contracts (Slutzky and Zeume, 2023). In support, Fenizia and Saggio (2024) reveal that municipal councils dismissal due to Mafia infiltration boost employment, the number of enterprises, and industrial real estate values. More in general, according to Acemoglu et al. (2020), during the 1970s, areas of Sicily with a high density of Mafia members experienced a decline in the number of individuals graduating from high school and a reduction in access to various public commodities. The existence of organized crime at the community level has a detrimental effect on the educational achievement of elementary school students (Cavalieri et al., 2023). The authors explain this outcome suggesting that the influence of the Mafia has a

negative impact on educational results by changing the incentive of young people (and/or their parents) to engage in school. It also discourages local firms from employing individuals who prioritize investing in human capital.

Criminal activities can significantly undermine trust, which is the foundation of financial agreements (Arcuri and Levratto, 2020). In the same way, the credit relationships between firms and financial institutions are contingent upon mutual confidence, and the presence of crime poses supplementary obstacles in the acquisition of financing and evaluating the corresponding risks. Empirical evidence provided by Gama et al. (2024) indicates that higher crime rates reduce the likelihood of firms adopting conservative financing practices. In detail, authors show that in municipalities with high crime levels, SMEs are less likely to avoid debt, showing more reliance on external financing, suggesting that crime presence may force firms to incur more debt, increasing bank risks in those areas. Indeed, crime may result in a less stable and riskier economic environment, which could cause firms to resort to debt to address their economic challenges, supporting the hypothesis that financial institutions in high–crime areas face greater uncertainty and risk, altering their lending behaviors and potentially tightening credit conditions over time. In a similar vein, firms connected to organized crime tend to have higher bank debt levels and a greater probability of default. As Bianchi et al. (2022) note, this heightened risk perception among banks may lead them to adopt stricter credit policies or impose more stringent lending conditions when dealing with firms in areas heavily influenced by criminal organizations.

Credit allocation is not immune to the adverse impacts of a negative en-

vironment, which can undermine its critical role in promoting growth and investment while also incentivizing entrepreneurial activity within the complex network of economic interactions. Actually, in a country like Italy, where the presence of small and medium–sized firms (SMEs) is substantial, bank credit is decisive for growth since SMEs' growth is significantly affected not only by age and size but also by credit rationing, as shown by Becchetti and Trovato (2002). Although organized crime can influence credit allocation, there have been few empirical studies that specifically look into this dysfunction. Banks operating in areas with a high level of organized crime face increased credit risk due to the distorting influences exerted by criminal syndicates on borrowers. Indeed, understanding the mechanisms that link organized crime to credit rationing is critical for developing effective policies that promote inclusive access to credit and long-term economic development. In this regard, Tarantola (2012) argues that banks operating in areas plagued by criminal organizations face difficulties in evaluating firms' creditworthiness, resulting in requests for additional guarantees. Within this field, the purpose of the present study is to contribute to the extant body of knowledge by examining whether the perception of organized crime influence could increase the likelihood of credit rationing. This study is founded upon a unique dataset obtained from a representative survey carried out by the Bank of Italy. The survey entails the involvement of almost 3000 industrial and service companies and focuses on three primary risks associated with the perception of crime. In order to substantiate this correlation with empirical data, we put forth four distinct models that represent firms' performance and credit rationing with varying specifications. The following constitutes

the structure of the reminder for this paper. Section 2 examines existing literature about the impact of organized crime and credit rationing on the economy. All the data and the variables used in the study are described in Section 3. Section 4 provides the empirical results and Section 5 concludes the study.

2. Background literature

The following subsection discusses the literature that shows that credit rationing has an impact on not only immediate access to credit but also investment decisions, consumption behavior, and overall economic growth. The other subsection discusses studies that have identified the economic consequences of organized crime.

2.1. Credit rationing

Credit rationing is a vital topic in economic research and has garnered significant attention in academic literature, as often loan markets reach equilibrium of credit rationing (Stiglitz and Weiss, 1981). Credit constraints significantly impact a firm's operational efficiency and its potential for growth. In countries where banking systems dominate, firms primarily finance their innovations through bank loans. For example, research by Piga and Atzeni (2007) indicates that firms with minimal or no investment in Research and Development (R&D) are less likely to seek additional funding. However, when these firms do apply for extra capital, they face a higher likelihood of credit denial. Similarly, Mancusi and Vezzulli (2014) found that credit rationing substantially affects both the likelihood of initiating R&D activities and the levels of investment in R&D.

Credit relationships are crucial, particularly for young and smaller firms seeking to navigate financial constraints. Berger and Udell (1995) highlight how the strength of a bank–firm relationship can directly affect the availability and terms of credit, particularly for smaller enterprises. Degryse and Van Cayseele (2000) found that while loan rates tend to increase with the duration of bank–firm relationships, the scope of these relationships significantly influences interest rates, suggesting a nuanced dynamic. Petersen and Rajan (1994) provide empirical evidence that long–term relationships facilitate better credit conditions and access for small businesses. Furthermore, Gobbi and Sette (2014) observed that post–Financial Crisis, firms with fewer, but more concentrated, banking relationships are less likely to experience a decrease in bank credit availability and are at a lower risk of credit rationing. Jiménez et al. (2012) examine how bank–specific characteristics and broader economic conditions influence credit supply, shedding light on how these factors are mediated through bank-firm relationships. Cenni et al. (2015) further demonstrated that although multiple banking relationships can heighten the risk of credit rationing for both small and large firms, a strong primary banking relationship is particularly advantageous for small firms, and sustained relationships tend to benefit all firms by potentially reducing credit rationing.

A stream of literature highlights that firm exports are related to credit provision; in this regard, Minetti and Zhu (2011) revealed that rationed firms have a 39% lower chance of exporting, and their foreign sales are reduced by more than 38%. This difficulty is faced mainly by high–tech industries and industries that heavily depend on external financing. Furthermore, Muûls

(2015) found evidence that Belgian manufacturing firms that are less credit–constrained have a higher probability of being exporters or importers.

2.2. The Role of organized crime in shaping market distortions

The impact or organized crime on the economy has always been a topic of interest through different fields of research. In particular, many studies focused on its consequences for firms and the economic system.

Mirenda et al. (2022) analyzed the effects of mafia infiltration in the legal economy. According to their study, mafia firms that enter the legal environment often follow an unconventional short–term business strategy that is centered on "exploiting the firm and depleting its assets". Moreover, Mirenda et al. (2022) consider money laundering, threats, violence, and corruption the reason which lies behind the better performance of dishonest firms in dominating the market and securing public contracts. As far as the effects on the public sector are concerned, Barone and Narciso (2015) showed that the presence of organized crime is positively related to the probability of obtaining public funds and that organized crime leads to episodes of corruption in the public administration sector. Furthermore, crime is a deterrent for foreign direct investments and job creation, in particular in less advanced transition countries (Krkoska and Robeck, 2006). Daniele and Marani (2011) confirms this effect for Italian provinces, arguing that an increase in the level of organized crime could be perceived as a sign of an unfavorable local socio–institutional environment for foreign direct investments. At the municipal level (specifically, in Calabria), Coniglio et al. (2010) showed that organized crime has a direct impact on the accumulation of human capital, either directly by reducing the incentive to invest in formal education or indirectly by

increasing migration outflows. Regarding some specific consequences on companies, Albanese and Marinelli (2013) found evidence that organized crime negatively affects productivity for both small and large enterprises, with a global adverse effect on the entire local economic and non–economic system, while Forgione and Migliardo (2023b) showed that the presence of criminal network pressure reduces firms' technical efficiency and their tendency to invest. Barbieri and Rizzo (2023) provided evidence that firm entry rates are negatively and sizable affected by the presence of crime: this may be considered a cost for the entrepreneur and it must be taken into account when calculating the social costs of crime. On the other hand, Le Moglie and Sorrenti (2022) demonstrated that the establishment of new enterprises has been less affected by the 2007 subprime mortgage crisis in provinces that have a higher organized crime presence.

A stream of literature has focused on the crucial role of fighting organized crime to improve the growth and the development of the economy. Slutzky and Zeume (2018) showed that anti–mafia enforcement measures are associated with an increase in competition between firms, innovation activity, and competition for public procurement contracts. Furthermore, Calamunci and Drago (2020) found evidence that boosting confiscation measures against criminal organizations has a significant positive impact on the economy, whereas Calamunci et al. (2021) provided evidence that getting involved in judicial administration can lead to a decrease in credit and a higher chance of experiencing credit rationing than in legal companies.

The presence of organized crime creates distortions in the market, resulting in an increase in the cost of doing business for companies and also poses

a threat to banks, which lend funds to finance firm activity. However, only a few studies have examined the impact of organized crime activities on credit lending. In particular, Bonaccorsi di Patti (2009) demonstrated that areas with elevated crime rates necessitate firms to pay increased interest rates, offer greater collateral, and rely less on asset–backed loans while favoring revolving credit lines compared to businesses in low–crime areas. This indicates that access to credit is negatively impacted by crime and that crimes impacting the loan market are those that externally heighten firm vulnerability and elevate loss given default. Another important contribution to the relationship between crime and credit is provided by de la Miyar (2016), which found evidence that Mexican Drug War drove to a drop of 3.2% in commercial credit granted to businesses. In this case, it is important to state that Mexico's organized crime activities are more violent and frequent than the Italian counterparts. Accordingly, this study aims to extend these results to understand if in Italy the presence of organized crime activities can lead banks to ration credit.

3. Data and variables

The estimates are performed by Bank of Italy's Remote Execution system (REX), which enables for the remote processing of data collected in the survey of industrial and service firms (INVIND Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]), regarding to nearly 3,000 enterprises. Typically, organized crime is under reported due to the potential consequences. An advantage related to the survey is that answers are anonymous: in this way, respondents can provide honest answers and they are not

identifiable. In addition, a lower risk of social bias and a higher participation rate improve the significance of the study. Regarding the dependent variables referred to credit rationing, Bank of Italy asked if the respondent applied for new loans from banks or other financial intermediaries and which of the following situations firm encountered: Firm received the amount requested; Firm was granted only part of the amount requested; Firm was given no loan because the financial intermediaries contacted were not willing to grant the loan. These questions lead to the variables used in this study. The first one (*Rationing*) is a dummy variable which takes the value 1 if the company was rationed and 0 otherwise. The second one (*Ordered rationing*) is a categorical variable which identifies if the enterprise obtained funds requested, obtained a part of the amount requested or did not obtain the loan at all. Then, as regards the main independent variable of the model, Bank of Italy asked how likely the owner of a firm in the same geographic area and economic sector as the respondent had encountered one of the following situations: Obtained a loan outside official channels – *Organized crime* $risk_1$; Received an offer to sell their business at unusual conditions – *Organized crime* $risk_2$; Been the object of threats, intimidation or extortion attempts – *Organized crime* $risk_3$. The survey respondents could answer in four ways: not all likely, unlikely, somewhat likely, and very likely. The proposed cross–sectional models (logit and ordered logit), referred to 2020, are specified as follows:

$$\begin{aligned} Pr(Rationing_i = 1) = F(&\beta_0 + \beta_1 Organized\,crime\,risk_{ij} + \beta_2 Size_i \\ &+ \beta_3 Age_i + \beta_4 Geo\,area_i + \beta_5 Performance_i \\ &+ \beta_6 Macro\,sector_i + \beta_7 Export\,share_i) \end{aligned} \tag{1}$$

$$
\begin{aligned}
Pr(Ordered\,rationing_i = w) = Pr(k_{w-1} < \beta_0 + \beta_1 Organized\,crime\,risk_{ij} \\
+ \beta_2 Size_i + \beta_3 Age_i + \beta_4 Geo\,area_i \\
+ \beta_5 Performance_i + \beta_6 Macro\,sector_i \\
+ \beta_7 Export\,share_i + u_i < k_w)
\end{aligned}
\tag{2}
$$

where dependent variables are respectively the probabilities of being rationed and of falling into one of the three categories (w) included in *Ordered rationing*, whereas *Organized crime risk*$_j$ is the main independent variable of the model and represents the organized crime perception indexes. We include a set of control variables commonly used in literature about credit. They consist in firm *Size*, that is a categorical variable made up by six categories referred to the total number of workers, *age* which represents how many years the firm has been in business (Petersen and Rajan, 1994, Agostino et al., 2009) and *Geo area* which is a multinomial variable that provides information about the headquarter of the firm, to capture the potential geographic effect on credit rationing. We also include two alternative variables to measure a firm's *Performance* (i.e. *Operating result*, a multinomial variable, and *Technical efficiency*, estimated through stochastic frontier analysis, as described in the Appendix), *Macro sector* that is a categorical variable which indicates the business the enterprise is involved in, and the export share, a multinomial variable that distinguishes different categories of the export share as a percentage of the turnover. $F(z) = e^z/(1+e^z)$ is the cumulative logistic distribution, u is assumed to be logistically distributed in ordered logit and k are the cutpoints. Table 1 provides definitions of all the variables used in this study while summary statistics are reported in Table 2.

[Tables 1 and 2 about here]

4. Empirical Results

The empirical findings, reported in Table 3, in which *Rationing* and *Technical efficiency* are considered, show that only the *Organized crime* $risk_3$ is statistically significant (at 1%) in affecting the probability of being credit rationed. More specifically, the odds–ratio explains that a high perception of threats, intimidation or extortion presence increases the probability of facing credit rationing by more than 124%. In these models, control variables are not statistically significant, with the exception of the macro sector referred to energy extraction: this implies that companies operating in this sector face a higher probability of being rationed than firms operating in the manufacturing sector.

[Table 3 about here]

Results reported in Table 4, in which we consider *Operating result* to evaluate firms' performance, show substantially the same outcomes. Even in these models, only a relevant perception of threats, intimidation or extortion presence increases the probability of not obtaining loans (in this case by 90%). Control variables show the same results, except for firms' *Performance*. In this case, facing small or large losses increases by far the probability of being credit rationed.

[Table 4 about here]

Empirical results reported in Table 5, in which *Ordered rationing* and *Technical efficiency* are considered, show that all of the three risks are statistically

significant in increasing the probability of being credit rationed. It implies that also a high perception of loans outside official channels and offers to sell business at unusual conditions presence increases the probability of facing credit rationing. Only in the model which considers the *Organized crime* $risk_2$, we found that firm's *Size* is statistically significant in decreasing the probability of being rationed. Overall, it is important to consider that the first class of this variable is referred to companies with 20–49 workers: this implies that we are considering a sample of firms with some reliability. We found also a non–linear statistically significant effect for firm's *Age* on the probability of facing credit rationing. Nevertheless, odds–ratios suggest that the impact of the square term is substantially irrelevant, whereas the linear term suggests that being older leads to a decrease in the probability of being credit rationed by approximately 3%. Furthermore, we found that the most efficient companies face a lower probability of being credit rationed by 2%: this is statistically significant at 5%. Also in these models, companies in energy extraction sector face a higher probability of being credit rationed than the manufacturing ones; on the other hand, exporting firms, face a decrease in the probability of being rationed rather than non–exporting ones.

[Table 5 about here]

Empirical findings reported in Table 6, in which we consider *Operating result* to evaluate a firm's performance, show similar results. In particular, with this specification, just the *Organized crime* $risk_3$ results statistically significant in increasing the probability of facing credit rationing (by 29%). Even in this case, control variables confirm what we have found in the previous models.

[Table 6 about here]

Our results corroborate previous findings provided by Bonaccorsi di Patti (2009) and de la Miyar (2016). Indeed, we found that the perception of organized crime presence plays a crucial role in banks' behaviour when they have to decide to grant loans or not. In particular, the organized crime risk referred to the presence of threats, intimidation or extortion results always statistically significant in impairing credit access. These findings may suggest that banks grant less loans due to the fear that companies might be out of business or deteriorate their position. Our other results confirm previous literature; in particular, younger and smaller firms face a higher probability of being rationed (Petersen and Rajan, 1994, Agostino et al., 2009). As expected, the more efficient and profitable firms are, the lower is the probability of getting credit rationed.

5. Concluding remarks

Organized crime has long influenced social and economic progress across different nations, with Italy standing as a prominent example. The intricate web of challenges associated with criminal organizations poses a continual hurdle for both governmental bodies and society at large. The ramifications of illicit activities extend to the economy, public safety, and overall social advancement, exerting a substantial impact on these crucial aspects of development. On the other hand, credit access plays a pivotal role in firms' growth and understand the complex dynamics of credit rationing and its implications is crucial for both borrowers and lenders. The presence of organized crime might lead to a worsening in credit supply due to the risk and the fear that firms face risk referred to organized crime. This study aimed

to contribute to the existing body of research by linking these two key factors in the development and growth of the economy, to understand the role organize crime plays in credit dynamics. Our results contribute to the prior literature by extending the findings of Bonaccorsi di Patti (2009) and de la Miyar (2016), by using a unique dataset provided by the Bank of Italy, which directly asked to industrial and service firms about the perception of organized crime presence. We have found evidence that the presence of organized crime makes credit access more difficult for firms. Specifically, operating in areas with higher perception of threats, intimidation or extortion improves significantly the probability of being rationed by credit institutions. Therefore, fighting organized crime is a priority for the society and firms well–being to contribute to the growth and development of the country. Policymakers and people have to face this difficult challenge which for too long has slowed socio–economic development.

Appendix

This study estimates technical efficiency of producing firm output by relying cross–sectional stochastic frontier analysis. The output is given as follows:

$$y_i = \alpha + x_i'\beta + \nu_i - \upsilon_i \tag{3}$$

where y_i represents the output of the ith firm, x' a vector of explicative variables (i.e. inputs) and β the relative technology parameters. The error term is the sum of the common white noise term (ν), which follows a normal distribution with zero mean and homoskedastic standard deviation, and the inefficiency is defined by a deviation from the maximum output achievable

with the inputs (υ) that has to conform to an exponential distribution. The stochastic production function is assumed to be trans–logarithmic, as follows:

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

where Q is the output proxied by the turnover. R, L and K are the three inputs: the first one is the production cost, the second one is the total staff expense and the last one is the capital stock. However, due to privacy restrictions, capital stock is not actually included in the dataset. As a consequence, and following Forgione and Migliardo (2023a), we follow the perpetual inventory method as described below (Berlemann and Wesselhöft, 2014):

$$k_{\alpha,t} = \sum_{i=0}^{\infty} (1-\delta_\alpha)^i I_{\alpha,t-(i+1)} \quad k_{\beta,t} = \sum_{i=0}^{\infty} (1-\delta_\beta)^i I_{\beta,t-(i+1)}$$

$$k_{\gamma,t} = \sum_{i=0}^{\infty} (1-\delta_\gamma)^i I_{\gamma,t-(i+1)} \quad k_{\xi,t} = \sum_{i=0}^{\infty} (1-\delta_\xi)^i I_{\xi,t-(i+1)}$$

$$k_{\eta,t} = \sum_{i=0}^{\infty} (1-\delta_\eta)^i I_{\eta,t-(i+1)}$$

where α represents company's investment in building, β in plants, machinery, and equipment, γ in means of transport, ξ the total amount spent on software and databases, and η the amount spent on research and development. The depreciation rates are in line with the relevant coefficients specified in the fiscal rule. Finally, k_i represents the accumulation of tangible and intangible asset capital stock investments over time, weighted by depreciation rates. The sum of these sub–capital stocks represents the total capital stock (K) for company i, which is utilized in the stochastic frontier analysis. In conclusion, technical efficiency scores, which range between 0 (total inefficiency) and 1

(total efficiency), are obtained by using the estimator proposed by Battese and Coelli (1988). Technical efficiency is defined as the ratio between the firm's mean production, given its realized effect, and the corresponding mean production if this effect was zero. It is shown in the following equation:

$$TE_i = \frac{E(y_i^*|u_i, x_i)}{E(y_i^*|u_i = 0, x_i)} \tag{4}$$

Table 7 provides coefficients and standard errors of the frontier performed to estimate technical efficiency.

[Table 7 about here]

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Table 1: Variables description

Variable name	Type	Description
Rationing	Dummy variable	It takes 1 if firm is rationed, 0 otherwise
Ordered Rationing	Multinomial variable	It takes 0 if the firm obtained funds requested, 1 if it partially obtained the amount requested, 2 if the loan is not granted
Organized crime risk$_{123}$	Multinomial variable	How likely is Usury, Dispossession and Extortion? [1]
Class 1		Not at all likely
Class 2		Unlikely
Class 3		Somewhat likely
Class 4		Very likely
Size [2]	Multinomial variable	Six categories
Geo Area	Multinomial variable	
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		Firm headquarter in the South of Italy
Age	Continuos variable	Difference between year of the survey and year of establishment
Operating result [3]	Multinomial variable	Five categories
Technical efficiency	Continuos variable	Technical efficiency estimated by rely on stochastic frontier analysis[4]
Macro Sector	Multinomial variable	
Category 1		Manufacturing
Category 2		Energy extraction
Category 3		Non–financial private services
Export share	Multinomial variable	
Category 0		Non–exporting firms
Category 1		Firm exporting less than 1/3 of their turnover
Category 2		Firm exporting between 1/3 and 2/3 of their turnover
Category 3		Firm exporting more than 2/3 of their turnover

[1] See the paper for more details

[2] 0=20–49; 1=50–99; 2=100–199; 3=200–499; 4=500–999; 5=1000 worker or more

[3] 1=Large profit; 2=Small profit; 3=Broad balance; 4=Small loss; 5=Large loss

[4] See the Appendix for more details

Table 2: Summary statistics

Variable	Num. Obs.	Mean	Std. Dev.	Min	Max
Rationing	1345	0.019	0.138	0	1
Ordered Rationing	1328	0.139	0.398	0	2
Organized crime risk$_1$	1345	1.484	0.76	1	4
Organized crime risk$_2$	1343	1.502	0.765	1	4
Organized crime risk$_3$	1340	1.355	0.64	1	4
Size	1345	1.544	1.424	0	5
Geo Area	1345	2.667	1.135	1	4
Age	1345	39.5	24.26	...	...
Operating result	1345	2.613	1.262	1	5
Technical efficiency	1090	83.793	7.94	...	...
Macro sector	1345	1.586	0.894	1	3
Export share	1345	1.246	1.07	0	3

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

Table 3: Logit model with Rationing as dependent variable and Technical efficiency.

	(I)	(II)	(III)
Dependent variable	Rationing	Rationing	Rationing
	Odds–ratio	Odds–ratio	Odds–ratio
Organized crime risk$_1$	1.482(0.388)		
Organized crime risk$_2$		1.321(0.339)	
Organized crime risk$_3$			2.242***(0.533)
Size	0.85(0.167)	0.835(0.161)	0.855(0.156)
Northwest		Benchmark	
Northeast	0.792(0.521)	0.806(0.527)	0.918(0.67)
Centre	0.674(0.45)	0.672(0.446)	0.855(0.586)
South	0.53(0.361)	0.55(0.365)	0.594(0.426)
Age	0.978(0.02)	0.979(0.019)	0.981(0.021)
Age^2	1(0)	1(0)	1(0)
Technical efficiency	1.009(0.025)	1.009(0.024)	1.011(0.027)
Manufacturing		Benchmark	
Energy extraction	12.784***(11.51)	12.92***(11.823)	9.961**(9.301)
Non–financial private services	1.818(1.096)	1.848(1.115)	1.756(1.041)
Non–exporting firm		Benchmark	
Less than 1/3 of turnover exported	0.552(0.398)	0.565(0.406)	0.523(0.374)
Between 1/3 and 2/3 of turnover exported	0.599(0.598)	0.626(0.621)	0.595(0.585)
More than 2/3 of turnover exported	1.692(1.205)	1.677(1.21)	1.69(1.212)
Intercept	0.012(0.035)	0.015(0.042)	0.004(0.013)
Number of observations	1090	1090	1087

Robust standard errors are reported in parentheses and are clustered at firm level, *p<0.10, **p<0.05, ***p<0.01

Table 4: Logit model with Rationing as dependent variable and Operating result.

	(I)	(II)	(III)
Dependent variable	Rationing	Rationing	Rationing
	Odds–ratio	Odds–ratio	Odds–ratio
Organized crime risk$_1$	1.25(0.323)		
Organized crime risk$_2$		1.178(0.301)	
Organized crime risk$_3$			1.904***(0.472)
Size	0.894(0.163)	0.882(0.153)	0.906(0.155)
Northwest		Benchmark	
Northeast	0.932(0.63)	0.932(0.628)	1.058(0.793)
Centre	1.07(0.654)	1.072(0.656)	1.328(0.871)
South	0.726(0.486)	0.733(0.483)	0.845(0.611)
Age	0.981(0.019)	0.981(0.019)	0.985(0.02)
Age^2	1(0)	1(0)	1(0)
Large profit		Benchmark	
Small profit	5.979*(5.871)	5.943*(5.853)	4.871*(4.68)
Broad balance	4.634(5.062)	4.667(5.115)	4.293(4.53)
Small loss	7.602*(8.072)	7.682*(8.177)	6.717*(7.004)
Large loss	14.088***(14.206)	14.354***(14.443)	11.091**(11.028)
Manufacturing		Benchmark	
Energy extraction	11.6***(9.552)	11.643***(9.703)	8.422**(7.518)
Non–financial private services	1.15(0.651)	1.154(0.654)	1.133(0.637)
Non–exporting firm		Benchmark	
Less than 1/3 of turnover exported	0.356(0.251)	0.356(0.252)	0.359(0.249)
Between 1/3 and 2/3 of turnover exported	0.503(0.409)	0.513(0.417)	0.51(0.417)
More than 2/3 of turnover exported	1.058(0.679)	1.049(0.676)	1.093(0.703)
Intercept	0.006***(0.009)	0.006***(0.01)	0.003***(0.005)
Number of observations	1345	1343	1340

Robust standard errors are reported in parentheses and are clustered at firm level, *p<0.10, **p<0.05, ***p<0.01

Table 5: Ordered logit model with Ordered rationing as dependent variable and Technical efficiency.

	(I)	(II)	(III)
Dependent variable	Ordered rationing	Ordered rationing	Ordered rationing
	Odds–ratio	Odds–ratio	Odds–ratio
Organized crime risk$_1$	1.318**(0.153)		
Organized crime risk$_2$		1.241*(0.147)	
Organized crime risk$_3$			1.384**(0.187)
Size	0.893(0.066)	0.885*(0.065)	0.887(0.065)
Northwest		Benchmark	
Northeast	0.773(0.237)	0.785(0.24)	0.799(0.248)
Centre	0.658(0.193)	0.666(0.197)	0.689(0.204)
South	0.772(0.225)	0.798(0.232)	0.795(0.234)
Age	0.97***(0.01)	0.971***(0.01)	0.972***(0.01)
Age^2	1**(0)	1**(0)	1**(0)
Technical efficiency	0.982**(0.009)	0.981**(0.009)	0.982**(0.009)
Manufacturing		Benchmark	
Energy extraction	4.52***(2.229)	4.53***(2.254)	3.858***(1.932)
Non–financial private services	1.154(0.286)	1.159(0.288)	1.158(0.288)
Non–exporting firm		Benchmark	
Less than 1/3 of turnover exported	0.595*(0.167)	0.592*(0.167)	0.582*(0.165)
Between 1/3 and 2/3 of turnover exported	0.845(0.283)	0.867(0.292)	0.853(0.288)
More than 2/3 of turnover exported	1.129(0.354)	1.106(0.349)	1.113(0.351)
Cut1	-0.329(0.931)	-0.441(0.926)	-0.256(0.937)
Cut2	1.602(0.927)	1.486(0.922)	1.718(0.926)
Number of observations	1078	1078	1076

Robust standard errors are reported in parentheses and are clustered at firm level, *p<0.10, **p<0.05, ***p<0.01

Table 6: Ordered logit model with Ordered rationing as dependent variable and Operating result.

	(I)	(II)	(III)
Dependent variable	Ordered rationing	Ordered rationing	Ordered rationing
	Odds–ratio	Odds–ratio	Odds–ratio
Organized crime risk$_1$	1.183(0.128)		
Organized crime risk$_2$		1.171(0.13)	
Organized crime risk$_3$			1.292**(0.166)
Size	0.893*(0.061)	0.889*(0.061)	0.893*(0.061)
Northwest		Benchmark	
Northeast	0.975(0.269)	0.98(0.27)	1.003(0.28)
Centre	0.746(0.204)	0.756(0.208)	0.783(0.217)
South	0.899(0.245)	0.896(0.244)	0.905(0.248)
Age	0.975***(0.008)	0.974***(0.008)	0.975***(0.008)
Age^2	1**(0)	1**(0)	1**(0)
Large profit		Benchmark	
Small profit	1.434(0.456)	1.425(0.454)	1.394(0.434)
Broad balance	1.8(0.667)	1.727(0.646)	1.715(0.635)
Small loss	2.958***(1.031)	2.948***(1.028)	2.929***(1.005)
Large loss	3.984***(1.382)	3.998***(1.386)	3.919***(1.344)
Manufacturing		Benchmark	
Energy extraction	3.857**(2.009)	4.001***(2.091)	3.379**(1.785)
Non–financial private services	1.06(0.238)	1.093(0.246)	1.082(0.243)
Non–exporting firm		Benchmark	
Less than 1/3 of turnover exported	0.589**(0.149)	0.594**(0.151)	0.596**(0.153)
Between 1/3 and 2/3 of turnover exported	0.751(0.229)	0.78(0.239)	0.78(0.24)
More than 2/3 of turnover exported	0.961(0.278)	0.978(0.283)	0.976(0.285)
Cut1	1.772(0.551)	1.758(0.554)	1.894(0.548)
Cut2	3.737(0.564)	3.716(0.568)	3.882(0.554)
Number of observations	1328	1327	1324

Robust standard errors are reported in parentheses and are clustered at firm level, *p<0.10, **p<0.05, ***p<0.01

Table 7: Stochastic frontier estimates.

	$\ln[Q_i]$
$\ln[R_i]$	$0.766^{***}(0.009)$
$\ln[L_i]$	$0.176^{***}(0.011)$
$\ln[K_i]$	$0.042^{***}(0.006)$
$\frac{1}{2}(\ln[R_i])\times(\ln[L_i])$	$-0.349^{***}(0.119)$
$\frac{1}{2}(\ln[R_i])\times(\ln[K_i])$	$-0.024^{***}(0.004)$
$\frac{1}{2}(\ln[L_i])\times(\ln[K_i])$	$0.031^{***}(0.007)$
$\frac{1}{2}(\ln[R_i])^2$	$0.181^{***}(0.004)$
$\frac{1}{2}(\ln[L_i])^2$	$0.158^{***}(0.011)$
$\frac{1}{2}(\ln[K_i])^2$	$0.006^{***}(0.002)$
Interecept	$12.004^{***}(0.013)$

Number of observations: 2486. Standard errors are reported in parentheses, *p<0.10, **p<0.05, ***p<0.01