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Essays on Efficiency in Banking and Financial Intermediation

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Declaration of Authorship

I, Marco SPADARO, declare that this thesis titled, "Essays on Efficiency in Banking and Financial Intermediation" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
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UNIVERSITY OF MESSINA

Abstract

Department of Economics

Doctor of Philosophy

Essays on Efficiency in Banking and Financial Intermediation

by Marco SPADARO

The study of efficiency in banking and financial intermediation is a key research topic with broad implications for financial stability, institutional profitability, and economic growth. Banking efficiency strengthens resilience, fosters competition, and improves credit availability, while firm–level efficiency plays a crucial role in shaping access to finance. Understanding these dynamics is essential not only for academic research, but also for practitioners and policymakers. This thesis employs Stochastic Frontier Analysis to evaluate both efficiency scores and their determinants and it is structured around four essays, each addressing a distinct dimension of efficiency in banking and financial intermediation.

In Chapter 1 the link between bank efficiency and liquidity creation is investigated through a Bayesian Stochastic Frontier Analysis. Results show that technical efficiency plays a key role in transforming deposits into loans.

In Chapter 2 the impact of the adoption of United Nations Principles for Responsible Banking on Euro Area banks' efficiency is examined. The findings suggest that sustainable practices aligned with core banking activities enhance resource utilization and foster long–term resilience.

In Chapter 3 the effect of organized crime on the efficiency of Italian cooperative banks is analyzed. Results reveal that banks located in areas with high criminal presence experience significant declines in both technical and cost efficiency.

In Chapter 4 the influence of perceived organized crime on firms' access to finance is analyzed using survey data from the Bank of Italy covering all economic sectors. The evidence shows that areas and industries more exposed to extortion, threats, and intimidation face tighter credit rationing, while more efficient firms exhibit lower probability of being credit rationed.

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This dissertation is dedicated to all those who have always been there to remind me of the bright spots, even during the hardest moments of this journey.

Contents

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List of Abbreviations

BSFA	**B**ayesian **S**tochastic **F**rontier **A**nalysis
CCBs	**C**redit **C**ooperative **B**anks
CEO	**C**hief **E**xecutive **O**fficer
CSP	**C**orporate **S**ocial **P**erformance
CSR	**C**orporate **S**ocial **R**esponsibility
DEA	**D**ata **E**nvelopment **A**nalysis
DMU	**D**ecision **M**aking **U**nit
EPs	**E**quator **P**rinciples
ESG	**E**nvironmental, **S**ocial (and) **G**overnance
GDP	**G**ross **D**omestic **P**roduct
GMM	**G**eneralized **M**ethod (of) **M**oments
M&As	**M**ergers (and) **A**cquisitions
NZBA	**N**et–**Z**ero **B**anking **A**lliance
OLS	**O**rdinary **L**east **S**quares
PRB	**P**rinciples (for) **R**esponsible **B**anking
R&D	**R**esearch (and) **D**evelopment
REX	**R**emote **Ex**ecution System
ROA	**R**eturn **O**n **A**ssets
ROE	**R**eturn **O**n **E**quity
SDGs	**S**ustainable **D**evelopment **G**oals
SFA	**S**tochastic **F**rontier **A**nalysis
SMEs	**S**mall (and) **M**edium **E**nterprises
SYS–GMM	**S**ystem **G**eneralized **M**ethod (of) **Moments**
TUB	**T**esto **U**nico **B**ancario
UNEP–FI	**U**nited **N**ations **E**nvironment **P**rogramme **F**inance **I**nitiative

Dedicated to my Family…

Introduction

Efficiency in banking and financial intermediation plays a crucial role in ensuring that financial resources are allocated productively and that the financial system remains sound and resilient. An efficient financial sector transforms savings into investment, supports innovation, and enhances economic growth. By contrast, inefficiencies in banking can amplify vulnerabilities, misallocate capital, and hinder access to finance, with adverse effects on both firms and households.

From a theoretical perspective, bank efficiency captures how effectively institutions convert inputs–such as labor, capital, and funding–into outputs like loans, investments, and financial services. Beyond being a measure of managerial performance, efficiency is a key determinant of stability and growth (Hasan et al., 2009; Belke et al., 2016). More efficient banks operate with lower costs, manage risks more effectively, and are better able to support credit supply during downturns. This makes efficiency a central component of both microprudential soundness and macroeconomic stability.

At the systemic level, improvements in bank efficiency strengthen the transmission of monetary policy and foster more competitive and inclusive financial markets. Empirical research has shown that efficiency gains contribute to regional and national development by improving the flow of credit to productive sectors (Zhuang et al., 2019), reducing risk exposure (Fiordelisi et al., 2011), and enhancing investors' confidence in the banking system (Beccalli et al., 2006). In this sense, efficiency represents a bridge between institutional performance and the broader functioning of the economy.

The importance of efficiency also extends to the real sector. Firms that use resources efficiently are generally more productive and less financially constrained, improving the overall quality of bank portfolios and reducing credit risk. Hence, efficiency constitutes a two–way link between financial intermediaries and firms: efficient banks promote efficient firms, and efficient firms, in turn, reinforce financial stability.

Building on these foundations, this thesis investigates efficiency from multiple and complementary perspectives. It examines how efficiency shapes key aspects of financial intermediation, institutional behavior, and access to finance, using stochastic frontier approaches applied to both banking and firm–level data. The four essays that compose the thesis explore distinct but related questions concerning efficiency and its determinants, ranging from the internal performance of banks to the external environment in which they operate.

Taken together, the essays provide new evidence on how efficiency affects financial stability, resilience, and inclusion. By analyzing different channels–ranging from liquidity creation to sustainability practices, institutional quality, and firm–level financing constraints–this work aims to contribute to a more comprehensive understanding of efficiency as a cornerstone of modern financial intermediation and economic development.

Chapter 1

Bank Efficiency and Liquidity Creation in the Euro Area: A Bayesian Approach[1]

Abstract

This study delves into the complex relationship between bank efficiency and liquidity creation through a Bayesian Stochastic Frontier Analysis performed on a panel of banks from the Euro Area countries over the period 2014–2022. The findings offer nuanced insights into the factors that influence liquidity creation and highlight the role of technical efficiency in facilitating this process. Effective risk management and efficient resource utilization are crucial in determining a bank's ability to transform deposits into loans and increase overall liquidity, regardless of the bank's characteristics of size and capital. The results suggest that policymakers should focus on promoting best practices in bank management to not only stabilize the banking sector but also extend credit to the broader economy.

1.1 Introduction

Technical efficiency expresses the ability of a bank to achieve the optimal frontier given a set of inputs and might therefore be a forerunner of bank performance. Efficiency allows banks to allocate resources more effectively, minimize waste, and mitigate various risks. In this sense, efficiency can help

[1]Parts of this chapter have been published in *Economics Letters* as: [Antonio Fabio Forgione, Carlo Migliardo, Marco Spadaro] (2025), "Bank Efficiency and Liquidity Creation in the Euro Area: A Bayesian Approach", in [Economics Letters], Volume 247, 112101, DOI: https://doi.org/10.1016/j.econlet.2024.112101.

alleviate liquidity constraints by enhancing banks' capacity to transform assets and liabilities efficiently. From this perspective, central banks could adopt a more tolerant stance toward efficient institutions, as these banks are perceived to be more reliable when managing systemic risk. Consequently, examining how bank efficiency impacts financial intermediation functions–particularly liquidity creation–has become increasingly critical.

In this context, liquidity refers to the bank's ability to meet its short–term obligations and withdrawal demands without incurring losses, as well as its role in transforming illiquid assets into liquid liabilities. Liquidity creation, therefore, describes the process through which banks convert illiquid loans and securities into liquid instruments such as deposits, which can be readily used by households and firms (Berger and Bouwman, 2009). This process is crucial not only for the stability and resilience of individual banks–by ensuring they can withstand funding pressures–but also for the broader economy, as it supports credit expansion, investment, and the effective transmission of monetary policy. Hence, a bank's capacity to create liquidity represents a key component of its intermediation function and contributes directly to financial and economic stability. Because liquidity creation depends on how effectively banks manage resources and risks, efficiency can be regarded as a fundamental determinant of their ability to generate liquidity.

One of the key roles of banks is to generate liquidity. According to modern theory, banks play this important role in the economy and also engage in risk transformation. Liquidity creation is a core function of banks. The standard view holds that banks create liquidity by transforming illiquid assets into liquid liabilities (Berger and Bouwman, 2009). With regard to risk transformation theories, banks convert risk by financing risky loans with riskless deposits (Boyd and Prescott, 1986). However, only a handful of studies have examined the effects of technical efficiency on banks' aptitude for creating liquidity. Referring to the effects of potential bank M&As on cost–side efficiency, Baltas et al. (2017) show that a rise in a bank's cost efficiency in UK and Greece beyond the consolidated level in the banking market leads to an increase in its liquidity creation. However, conventional stochastic frontier approaches assume that all banks operate relative to a common frontier with the vertical gap representing inefficiency. If banks have identical production possibilities, the conventional stochastic frontier model is suitable. In practice, banks employ diverse technologies for various reasons; thus, a random coefficient stochastic frontier model can be used to distinguish firm–specific efficiency from technological differences across banks (Tsionas, 2002). Furthermore, Duan et al. (2021) applied two accounting based efficiency indicators for cost and profit efficiency to a panel of more than 150,000 banks from 112 countries and found that cost and profit efficiency positively influence banks' liquidity creation.

Moreover, very few studies of the banking industry have exploited the advantages of the Bayesian approach to Stochastic Frontier Analysis (SFA) (e.g., Tecles and Tabak, 2010; Vu and Turnell, 2010; Maziotis et al., 2023), and none of these tested the relation of efficiency to bank liquidity creation. Bayesian techniques allow for accurate distributions of parameters or functions of interest to be computed without reliance on asymptotic approximations. This method also guarantees the thorough integration of parameter uncertainty by assigning a prior probability distribution to each parameter, mirroring the belief of the researchers (Griffin and Steel, 2007). It thus makes it possible to easily calculate posterior probabilities related to efficiencies.

Accordingly, this study contributes to the literature on the influence of operational efficiency on the capacity of banks to produce liquidity by exploiting the advantages of Bayesian Stochastic Frontier Analysis (BSFA).

The remainder of this paper is organized as follows. Section 1.2 describes the background literature, Section 1.3 the empirical strategy, Section 1.4 describes the data, Section 1.5 presents the empirical results, and Section 1.6 concludes the study.

1.2 Background literature

1.2.1 Bank liquidity creation

Drawing on the theoretical framework, this section reviews the existing literature on bank liquidity creation, efficiency, and their interrelation.

Banks play a pivotal role in the economy by increasing the availability of liquid financial resources through a combination of balance–sheet and off–balance sheet activities. In particular, this involves using deposits to fund loans, effectively transforming liquid resources into less liquid assets (Bryant, 1980; Diamond and Dybvig, 1983). Furthermore, instruments such as loan commitments and letters of credit significantly enhance banks' liquidity creation (Holmström and Tirole, 1998). In this vein, Kashyap et al. (2002) propose that loan commitments and similar claims on liquid funds help banks create off–balance sheet liquidity. This activity of banks is critical for stimulating economic activity, encouraging long–term investment, maintaining stability, instilling confidence in financial markets, and decreasing systemic risk (Bhattacharya and Thakor, 1993; Dell'Ariccia et al., 2008; Berger et al., 2017; Davydov et al., 2021). In addition, liquidity creation through both on– and off–balance sheet activities decreases non–performing loans (Alaoui Mdaghri, 2022). Besides, bank liquidity creation could be employed as a signal of recessions and financial crises, and it is procyclical, which means that banks create more liquidity during economic expansions (Berger and Bouwman, 2017; Chatterjee, 2018; Davydov et al., 2018; Niu, 2022). However, by financing their assets with short–term deposits and demand liabilities that generate imbalances in their maturity structures, banks can face illiquidity issues that can lead to bank runs and bank failures (Berger et al., 2009). Moreover, excessive liquidity creation by banks can become counterproductive, as surpassing a certain threshold is associated with a significantly higher risk of failure and systemic risk (Fungacova et al., 2021; Louhichi et al., 2024), whereas credit ratings purchases by banks and liquidity creation are negatively related (Kladakis et al., 2022b).

Over time, several approaches have been developed to measure liquidity creation. Deep and Schaefer (2004) firstly introduced a measure of bank liquidity creation, termed the "liquidity transformation gap", which is calculated as the ratio of the difference between liquid liabilities and liquid assets to total assets. Subsequently, Berger and Bouwman (2009) proposed their own measure of liquidity creation, commonly employed in literature, calculated using a three–step procedure that classifies all bank activities based on the facility, cost, and time required to raise cash, and aggregates these activities using assigned weights. This liquidity creation indicator has been slightly modified by Berger et al. (2019), to make the measure suitable also for international studies.

It is widely acknowledged that smaller financial institutions face challenges in accessing uninsured funding (Kashyap and Stein, 2000). Furthermore, there is an inverse causal effect between a bank's capital and liquidity generation (Diamond and Rajan, 2000; Diamond and Rajan, 2001; Horváth et al., 2014; Casu et al., 2019), which supports the financial fragility–crowding out hypothesis (Berger and Bouwman, 2009). In this vein, Van den Heuvel (2008) and Gorton and Winton (2017) have shown that a higher capital ratio diminishes the creation of liquidity. Bank capital can induce liquidity activity under the risk absorption hypothesis (Díaz and Huang, 2017) but this effect is mediated by bank size and specialization (Hsieh et al., 2022).

Several studies have examined a range of bank–related elements that affect liquidity generation. Possible determinants of bank liquidity transformation that have been stress tested in the literature are asset market liquidity (Chatterjee, 2015), regulatory interventions, capital support and regulatory stress tests (Berger et al., 2016; Nguyen et al., 2020), market competition (e.g., Jiang et al., 2019), bank ownership structure characteristics (Yeddou and Pourroy, 2020), interest rate shocks (Kick, 2022), CEO optimism and investor sentiment (Huang et al., 2018; Cai et al., 2023), and government guarantees (Berger et al., 2024). Wang et al. (2022) have shown that economic policy uncertainty hinders bank credit, while country governance mitigates this negative effect on bank liquidity creation. Furthermore, in countries with strong supervision policies banks create more liquidity than those in countries with tighter regulatory regimes (Kladakis et al., 2022a).

A relatively recent strand of the literature has focused on the effects of digitalization and climate on bank liquidity creation. Specifically, Hao et al. (2023) and Wu et al. (2024) have shown that digital finance development negatively affects banks' liquidity creation, with bank risk–taking acting as a mediating channel. Tao and Sun (2024) partially confirm this finding, showing a U–shaped relationship between digital credit and bank liquidity creation. This effect appears more pronounced during economic downturns and in highly marketized regions, with prudential supervision playing a significant moderating role. Indeed, fintech regulation facilitates bank liquidity creation (Liu et al., 2024). Climate sensitivity and exposure are found to negatively affect overall liquidity creation, whereas climate adaptation contributes positively (Lee et al., 2022). In this vein, Xu et al. (2024) indicate that climate policy uncertainty notably diminishes bank liquidity creation.

Studies of bank performance have presented mixed results on liquidity creation, with some analyses finding an indirect effect (e.g., Berger and Bouwman, 2009) and others finding a direct positive effect (e.g., Tran et al., 2021). The disparity in these findings may be attributed to the susceptibility of profitability measures to managerial tactics that influence the balance sheet or stock value and consequently affect accounting– or market–based indicators. Moreover, the creation of liquidity appears to be related to higher profitability during both normal times and financial crises, and both for large and small banks, with the creation of liquidity on the asset–side negatively associated to profitability, whereas the liquidity creation on liability–side and off–balance sheet is positively linked to profitability (Duan and Niu, 2020).

Overall, the literature underscores that liquidity creation is central to banks' intermediation role and financial stability. Yet, despite extensive work on its determinants, little attention has been paid to the role of bank efficiency in shaping this process.

1.2.2 Bank efficiency

The analysis of bank efficiency has received considerable attention as a means to evaluate how effectively banks utilize their inputs to produce financial services. The measurement of efficiency in the banking sector has evolved through SFA and DEA (Data Envelopment Analysis) (Berger and Humphrey, 1997; Fries and Taci, 2005; Casu and Girardone, 2006). Later contributions integrated institutional and environmental factors, recognizing that efficiency may depend on market structure and regulation (Lozano-Vivas and Pasiouras, 2010; Koetter et al., 2012).

Empirical research identifies several determinants of efficiency, including size, capitalization, market competition, ownership type, regulatory constraints, and technological change (Fiordelisi, 2007; Koutsomanoli-Filippaki et al., 2009; Chortareas et al., 2012). Digital transformation, for instance, has improved cost efficiency through automation and scale economies, whereas tighter regulation may temporarily limit efficiency gains.

Credit channel represents an important way to increase overall liquidity and create liquidity in the economic system. For this reason, it is crucial to highlight how a stream of literature has focused on the relationship between bank efficiency and credit. For instance, during financial crises bank efficiency relaxes credit constraints and increases the growth rate for financially dependent industries (Diallo, 2018). In this vein, Shamshur and Weill (2019) provide evidence that bank efficiency reduces the cost of credit for SMEs, but does not exert a significant influence for either micro companies or large firms. Furthermore, the effect is driven by large banks, where improvements in bank efficiency tend to be strongly associated with lower cost of credit. They also find that lower bank competition facilitates the transmission of greater bank efficiency to lower cost of credit. Overall, their results indicate that measures that increase bank efficiency can foster access to credit. International evidence provided by Osei-Tutu and Weill (2022) shows that greater bank efficiency improves access to credit for firms. The beneficial impact of bank efficiency to alleviate credit constraints takes place through the demand channel by reducing borrower discouragement to apply for a loan. Whereas the positive impact of bank efficiency on credit access is observed for firms of all sizes, the effect tends to be more pronounced in countries with a better economic and institutional framework. For what regards the lending channel in China, Fungáčová et al. (2023) suggest that bank efficiency may influence the bank lending channel in certain cases.

Overall, efficiency emerges as a fundamental determinant of banks' performance and resilience, with implications for their ability to perform core intermediation functions such as liquidity creation.

The potential link between bank efficiency and liquidity creation has recently attracted attention. From a theoretical perspective, more efficient banks may be better equipped to manage assets and liabilities, absorb shocks, and allocate funds toward liquidity-enhancing activities. Conversely, efficiency gains may also induce a more cautious risk posture, potentially reducing liquidity creation if banks prioritize stability over expansion.

Baltas et al. (2017) show that improvements in cost efficiency following bank mergers in the UK and Greece increase liquidity creation. Duan et al. (2021), analyzing over 150,000 banks in 112 countries, find that both cost and profit efficiency positively affect liquidity creation.

Although the existing literature provides useful insights, the interaction between bank efficiency and liquidity creation remains relatively underexplored. This strand of research continues to evolve, highlighting the importance of understanding how operational efficiency shapes the capacity of banks to perform liquidity creation while maintaining stability and resilience in the financial system.

1.3 Empirical strategy

Technical efficiency may be estimated by employing both parametric (SFA) and non–parametric (DEA) techniques. Stochastic production frontier models were independently proposed by Aigner et al. (1977), Battese and Corra (1977) and Meeusen and van Den Broeck (1977), while DEA has been introduced by Charnes et al. (1978). Stochastic frontier models are characterized by the assumption that all the deviations from the frontier represent firm specific inefficiency and that there is no economic agent which can exceed the ideal frontier (Belotti et al., 2013). On the other hand, DEA is a mathematical programming model that does not require any assumption about the production function and the inefficiency distribution. The choice of BSFA over DEA is grounded on the possibility to distinguish inefficiency from statistical noise. Pitt and Lee (1981) introduced the general stochastic model for longitudinal data, which can be expressed as in (1.1)

$$y_{it} = \alpha + \mathrm{x}'_{it}\beta + \nu_{it} - u_{it} \tag{1.1}$$

where y_{it} is the dependent variable and represents the logarithm of the output, α is the intercept, x'_{it} is a vector for the explanatory variables (inputs), β is a vector of parameters to be estimated, ν_{it} is measurement error and u_{it} is a non–negative disturbance which represents inefficiency.

This study estimates the technical efficiency of producing bank output by relying on a "true" random effects model that distinguishes time–varying efficiency from firm–specific time–invariant heterogeneity (Greene, 2005).

The output is given as follows:

$$y_{it} = \alpha + \mathrm{x}'_{it}\beta + \nu_{it} - \upsilon_{it} + w_i \tag{1.2}$$

where α is the constant, x' a vector explicative variables and β the relative parameters. The error term consists of two components: the common white noise term (ν_{it}), which is distributed with zero mean and homoskedastic standard deviation, and the inefficiency component (υ_{it}), which represents the deviation from the maximum achievable output given the inputs. It has been assumed that the inefficiency term follows a normal–exponential distribution, which is commonly adopted in Bayesian frameworks. The term w_i represents firm–specific random effects that account for unobserved heterogeneity across firms.

Compared to the classical SFA, the BSFA shows different advantages: it enables to determine the parameters' specifications and the model's ambiguity, include prior ideas, and accurate finite sample inference on efficiencies. BSFA requires the specification of priors for the parameters. In particular, β follows a multivariate normal distribution, where $\overline{\beta}$ is the vector of parameter means and Ω a positive–definite covariance matrix ($\beta \sim N(\overline{\beta}, \Omega)$). As usual in Bayesian framework, non–informative priors on the distributions of the coefficients have been imposed[2]. Conversely, the prior for the efficiency term, $\upsilon_{it} \sim Exp\,(\omega)$, is defined as follows $\omega \sim \Gamma\,(1, 1/5.19)$, that implies a

[2]In detail, the prior for σ^{-2} is specified as $f_G(\sigma^{-2}|0.5n_0, 0.5a_0)$. The hyperparameters n_0 and a_0 are set to 10^{-4}, defining a Gamma prior distribution on σ^{-2} close to the typical non–informative prior for small and moderate values of σ^{-2}.

prior median efficiency of 0.875 as in Van den Broeck et al. (1994) and Koop and Steel (2001)[3].

The stochastic production function is assumed to be trans–logarithmic, as follows:

$$\ln Q_{it} = \eta_0 + \sum_{k=1}^{3} \zeta_k lnP_{kit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \varrho_{kj} lnP_{kit} lnP_{jit} + (\nu_{it} - v_{it}) + \lambda_i \quad (1.3)$$

The output and the inputs employed in the production function are similar to that commonly used in the literature (Casu and Girardone, 2006; Degl'Innocenti et al., 2020; Algeri et al., 2022). Q_{it} is the output proxied by total assets, which captures the overall scale of banking activity. P_1, P_2 and P_3 are the three inputs: P_1 is the labor cost and it is obtained by the ratio between staff expense and interest margin. Labor is a crucial input for banks because banking activities largely depend on human expertise, relationship management, and the ability to assess and monitor risk, rather than on mechanical production processes. P_2 is the physical capital price and it is calculated as the ratio between the sum of other administrative expenses and other operating expenses over fixed assets. In the banking context, physical capital mainly includes branch networks, information technology systems, and infrastructure that enable the provision of financial services and the processing of transactions, instead of traditional manufacturing equipment. P_3 is the borrowed fund price and it is obtained as the ratio between total interest expense and total liabilities. This input reflects the cost of external funding, which is a core component of banks' production technology since banks transform deposits and other borrowed funds into loans and other earning assets. The inclusion of these three input prices follows the intermediation perspective, which views banks as financial intermediaries that use labor, physical capital, and borrowed funds to produce financial assets and services.

The two–step system–GMM (SYS–GMM) estimator is performed to evaluate the relationship between liquidity creation and a set of explanatory variables. This approach features a dynamic specification that addresses potential endogeneity issues by incorporating a set of instrumental variables and other exogenous variables, such as country inflation rates and country and year dummies. The main characteristics of the SYS–GMM estimator are described in Appendix A.

[3]The efficiency estimation follows the routine proposed by Makiela and Ouattara (2018). The Gibbs sampler is applied to obtain posterior distributions and consists of 25,000 cycles with a burn–in period of 10,000 iterations.

TABLE 1.1: Sample distribution by country and specialisation.

Country	Commercial	Savings	Cooperative
Austria	16	7	7
Belgium	2	1	1
Croatia	3	-	-
Cyprus	1	-	-
Finland	1	3	-
France	1	-	-
Germany	28	287	451
Greece	2	-	-
Ireland	1	-	-
Italy	36	6	163
Latvia	1	-	-
Lithuania	1	-	-
Luxembourg	8	1	-
Malta	1	-	-
Netherlands	4	-	-
Slovakia	1	-	-
Slovenia	7	-	-
Spain	1	2	7
Portugal	10	37	2

1.4 Data and variables

The analysis in this paper is performed on a balanced panel of 1,100 banks (commercial, savings, and cooperative) from countries within the Euro Area during the period 2014–2022. The study aims to evaluate the relationship between bank technical efficiency and liquidity creation across continental European banks. The balanced panel structure is required to perform the BSFA routine. Data are obtained from Orbis Bank Focus and refer to unconsolidated accounts with no consolidated companion and unconsolidated accounts with consolidated companion. The sample includes only active banks with complete data for all variables required in the efficiency and liquidity creation estimation over the entire observation period. Institutions with missing observations were excluded to ensure data consistency and comparability. The final sample is described by country and specialization in Table 1.1 and represents a balanced and homogeneous set of Euro Area banks suitable for the application of the BSFA.

The SYS–GMM model is shown in equation (1.4).

TABLE 1.2: Classification of bank activities as liquid, semiliquid or illiquid, and their weights.

Assets		
Illiquid assets (weight=1/2)	Semiliquid assets (weight=0)	Liquid assets (weight=-1/2)
Other mortgage loans Corporate and commercial loans Other loans Investment in property Other earning assets Foreclosed real estate Fixed assets Goodwill Other intangibles Current tax assets Deferred tax assets Discontinued operations Other assets	Residential mortgage loans Other consumer/retail loans Loans and advances to banks	Reserve repos and cash collateral Trading securities and at FV through income Available for sale securities Held to maturity securities At–equity investment in associates Other securities Cash and due from other banks Insurance assets
Liabilities and equity		
Liquid liabilities (weight=1/2)	Semiliquid liabilities (weight=0)	Illiquid liability and equity (weight=-1/2)
Customer deposits Deposits from banks Repos and cash collateral Trading liabilities	Other deposits and short–term borrowing	Senior debt maturing after 1 year Subordinated borrowing Other funding Fair value portion of debt Credit impairment reserves Reserves for pensions and other Current tax liabilities Deferred tax liabilities Other deferred liabilities Discontinued operations Insurance liabilities Other liabilities Pref. shares and hybrid capital accounted for as debt Pref. shares and hybrid capital accounted for as equity Common equity Non–controlling interest Securities revaluation reserves Foreign exchange revaluation reserves Fixed assets revaluation and accumulated OCI
Off–balance sheet		
Illiquid guarantees (weight=1/2)	Semiliquid guarantees (weight=0)	Liquid guarantees (weight=-1/2)
Guarantees Acceptances and documentary credits reported off–balance sheet Committed credit lines Other contingent liabilities	Other off–balance sheet exposure to securitizations	

$$
\begin{aligned}
LC/GTA_{it} = &\beta_0 + \beta_1 LC/GTA_{it-1} + \beta_2 TE_{it} + \beta_3 Size_{it} \\
&+ \beta_4 Cap_{it} + \beta_5 GDP_{it} + (\mu_i + \epsilon_{it})
\end{aligned}
\tag{1.4}
$$

The liquidity creation variable (LC) is computed using the methodology described by Berger and Bouwman (2009), with some modifications made by Berger et al. (2019) to ensure its applicability in international studies. This implies that bank activities are classified as liquid, semiliquid, or illiquid based on the time, ease, and cost for banks to meet liquidity demands and for customers to obtain liquid funds from the bank. Weights of $1/2$ and $-1/2$ are then assigned to all assets and liabilities, because only half of the liquidity created can be referenced to the use or source of funds. A weight of 0 is assigned to semiliquid activities. The analysis is performed on both *Cat fat* (including off–balance sheet activities) and *Cat nonfat* (excluding off–balance sheet activities) liquidity measures. The classification and weights reported in bank liquidity creation are normalized by dividing these measures on gross total assets. The classification of bank activities and their weights are reported in Table 1.2.

TABLE 1.3: Coefficients posterior mean and their standard deviation.

Variables	Posterior mean	Standard deviation
Labor	-1.221	0.579
Physical Capital	0.133	0.157
Borrowed Funds	-0.435	0.060
Labor × *Physical Capital*	-0.057	0.057
Labor × *Borrowed Funds*	0.084	0.017
Physical Capital × *Borrowed Funds*	0.026	0.019
Labor^2	0.316	0.172
Physical Capital^2	0.000	0.008
Borrowed Funds^2	-0.029	0.003
Intercept	16.039	0.849

Number of observations: 9,900.

The *TE* variable represents efficiency scores obtained as the draws posterior mean from efficiency posterior distribution estimated at firm level from the BSFA methodology and they are obtained as $r_{it} = e^{-u_{it}}$ (Van den Broeck et al., 1994). The coefficients posterior means and standard deviations are reported in Table 1.3.

The specification includes a set of control variables to control for confounding effects not captured by the fixed effect component or country dummies. First, it is well known that bank equity capitalization affects liquidity creation. According to Berger and Bouwman (2009), there are two conflicting assumptions concerning the relationship between a bank's capitalization and its ability to generate liquidity: the first is known as the "financial fragility–crowding out hypothesis" and posits a direct connection, whereas the second–the "risk absorption hypothesis"–suggests an inverse correlation. The *Cap* variable represents the Tier 1 capital ratio, which adjusts the bank's capitalization based on the risk level of its assets. Second, *Size* accounts for the influence of the bank's scale and it is defined as the logarithm of the number of employees. Third, the equation incorporates the variable *GDP* (Berger and Sedunov, 2017), which represents the annual growth rate of GDP at the national level for the country in which the bank is headquartered. Finally, the year dummies capture the dynamics of bank liquidity generation changes over time.

Table 1.4 provides definitions of the variables and reports the summary statistics.

TABLE 1.4: Variables description and their descriptive statistics.

Variable	Description	Minimum	Maximum	Mean	Standard deviation
Cat fat	Cat fat liquidity creation over gross total assets, winsorized at 1%.	-0.022	1.004	0.538	0.191
Cat nonfat	Cat nonfat liquidity creation over gross total assets, winsorized at 1%.	-0.051	0.802	0.492	0.181
TE	Technical efficiency scores, winsorized at 1%.	0.348	0.970	0.849	0.111
Size	Natural logarithm of the number of the employees, winsorized at 1%.	2.197	8.630	4.983	1.327
Cap	Core Tier 1 capital on total risk–weighted assets, winsorized at 1%.	9.342	50.850	17.492	6.414
GDP	Annual percentage growth rate of GDP (2015=100), winsorized at 1%.	-8.974	8.314	1.319	2.758

Macroeconomic variables are obtained from the World Development Indicators (World Bank).

1.5 Empirical results

The results reported in Table 1.5 validate the choice of a dynamic specification, as liquidity creation appears to be significant and persistent process[4].

Banks that excel in the strategic efficient management of their resources are able to create more liquidity. This may indicate that efficient banks follow better risk management strategies that enable them to minimize their cost burden and/or optimize their output, thus absorbing more risk and thereby generating more liquidity (Duan et al., 2021)[5]. Empirical findings largely support those of Berger and Bouwman (2009), who demonstrate a direct relationship between enhanced bank performance and increased liquidity generation. Accessing more stable and diversified funding sources enhances banks' ability to transform deposits into loans. Furthermore, proficient banks demonstrate an ability to manage their capital and financial risks more adeptly, thereby improving their capacity to create liquidity. Results are also consistent with those of Casu et al. (2019) in confirming the dominance of the financial fragility–crowding out assumption, as bank capital hampers bank liquidity creation. Furthermore, the results validate the assumption that bank size positively affects liquidity creation aptitude (Pham et al., 2021). The rejection of the autocorrelation test AR(1) and the non–rejection of autocorrelation test AR(2) provide evidence for the consistency of the GMM estimator, while the Hansen test confirms the validity of the instrumental variables employed in both specifications.

To further assess the practical relevance of these findings, the economic magnitude of the main variables is computed. Specifically, the effect of a one–standard–deviation change in each explanatory variable on liquidity creation,

[4]Several tests to rule out the presence of a unit root in the *LC* variable have been carried out, and the results were robust and statistically significant, supporting the hypothesis that the variable is stationary. Results of the unit–root tests are reported in Appendix A.

[5]Research by Baltas et al. (2017) utilizing a cost–efficiency model, even if in a context of potential M&A operations regarding banks, shows that increased cost efficiency leads to expanded liquidity.

TABLE 1.5: Results of SYS-GMM estimation.

Dependent variable	(1) *Cat fat*	(2) *Cat nonfat*
Independent variables		
$Cat\ fat_{t-1}$	0.893***(0.032)	
$Cat\ nonfat_{t-1}$		0.968***(0.039)
TE	0.165**(0.072)	0.134**(0.064)
$Size$	0.025*(0.014)	0.036*(0.019)
Cap	-0.004***(0.001)	-0.003**(0.001)
GDP	0.001(0.002)	-0.001(0.001)
$Intercept$	-0.154*(0.085)	-0.225*(0.115)
Country Dummies	Yes	Yes
Year Dummies	Yes	Yes
Number of instruments	52	52
Serial correlation test		
AR(1)	-6.65(*0.000*)	-7.43(*0.000*)
AR(2)	0.50(*0.616*)	0.97(*0.333*)
Hansen test	9.82(*0.981*)	13.00(*0.909*)

Number of observations: 8,800. (1) is referred to the model with *Cat fat* liquidity creation measure, (2) is referred to the other one. Standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%. For serial correlation tests, results are presented while values in italics reported in parentheses are p–values.

TABLE 1.6: Results of SYS-GMM estimation by specialisation.

Dependent variable	(1) *Cat fat*	(2) *Cat fat*	(3) *Cat fat*	(4) *Cat nonfat*	(5) *Cat nonfat*	(6) *Cat nonfat*
Independent variables						
$Cat\,fat_{t-1}$	0.631***(0.199)	0.982***(0.057)	0.861***(0.020)			
$Cat\,nonfat_{t-1}$				0.790***(0.234)	1.031***(0.067)	0.849***(0.031)
TE	0.427**(0.191)	0.200*(0.119)	0.327**(0.158)	0.156**(0.064)	0.205*(0.109)	0.266**(0.106)
Size	0.025(0.014)	-0.002(0.013)	-0.036*(0.022)	-0.019(0.012)	0.010(0.011)	-0.040**(0.016)
Cap	0.003(0.004)	-0.002(0.001)	-0.003(0.002)	0.004(0.004)	-0.000(0.001)	-0.004*(0.003)
GDP	-0.029***(0.011)	-0.006(0.004)	-0.002*(0.001)	0.006(0.007)	0.001(0.005)	-0.002(0.002)
Intercept	-0.520(0.385)	-0.172(0.130)	-0.002(0.115)	0.035(0.197)	-0.273*(0.150)	0.089(0.147)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of instruments	48	29	24	48	29	24
Serial correlation test						
AR(1)	-3.72(*0.000*)	-2.85(*0.004*)	-6.55(*0.000*)	-2.98(*0.003*)	-5.58(*0.000*)	-3.36(*0.001*)
AR(2)	-0.74(*0.461*)	0.40(*0.692*)	0.52(*0.602*)	-0.11(*0.916*)	-0.03(*0.977*)	0.85(*0.393*)
Hansen test	7.21(*0.981*)	1.74(*0.995*)	3.60(*0.731*)	8.63(*0.951*)	3.99(*0.912*)	6.80(*0.340*)
Number of observations	1,000	2,752	5,048	1,000	2,752	5,048

Models (1) and (4) are referred to commercial banks, models (2) and (5) are referred savings bank, models (3) and (6) are referred to cooperative banks. Standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%. For serial correlation tests, results are presented while values in italics reported in parentheses are p–values.

expressed in percentage points of the dependent variable, is evaluated. The results show that a one–standard–deviation increase in technical efficiency leads to an increase of approximately 1.78 percentage points in *Cat fat* and 1.45 percentage points in *Cat nonfat* liquidity creation. In comparison, a one–standard–deviation increase in bank size increases liquidity creation by 3.3 percentage points (*Cat fat*) and 4.76 percentage points (*Cat nonfat*), while a similar increase in capital decreases it by 2.56 percentage points and 1.92 percentage points, respectively. These findings indicate that improvements in technical efficiency have an economically meaningful impact on banks' ability to create liquidity. The magnitude of this effect is smaller than that of bank size but comparable in order of magnitude, and it acts in the opposite direction of capital.

To further examine the relationship between efficiency and liquidity creation across different bank types, Table 1.6 presents the results of the empirical models for different specialisation, confirming a positive and statistically significant link between banks' technical efficiency and the liquidity they create.

To corroborate the results, a robustness test is performed: it consists essentially in the same analysis but, in this case, efficiency scores are obtained through the traditional stochastic frontier model. The traditional trans–log

TABLE 1.7: Trans–log stochastic frontier coefficients.

Variables	Coefficient
Labor	-0.691***(0.160)
Physical Capital	0.156***(0.044)
Borrowed Funds	-0.423***(0.058)
Labor × *Physical Capital*	-0.058***(0.022)
Labor × *Borrowed Funds*	0.078***(0.025)
Physical Capital × *Borrowed Funds*	0.024**(0.010)
Labor^2	0.190***(0.040)
Physical Capital^2	-0.009(0.007)
Borrowed Funds^2	-0.030***(0.005)
Intercept	14.896***(0.352)

Number of observations: 9,900. Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

production function is specified as in equation 1.3. In Table 1.7 frontier coefficients and their standard errors are reported.

In Table 1.8 and Table 1.9 results of the SYS–GMM models in which technical efficiency is obtained through the standard stochastic frontier analysis are reported.

Results presented in Table 1.8 and Table 1.9 confirm previous findings and provide evidence about the positive relationship between banks technical efficiency and their ability to generate more liquidity. The validity of the estimation is further validate also in this case by the serial correlation and the Hansen tests.

1.6 Concluding remarks

Technical efficiency makes banks more effective in the allocation of resources, minimization of waste, and mitigation of risks. Banks play critical role in the economy by improving liquid financial resources. A large body of literature has stressed out different implications related to bank efficiency and liquidity creation, separately. Even though banks' technical efficiency and liquidity creation play crucial role in shaping banking activity and foster the overall economic system development, highlighting in particular how efficient banks increase credit availability, very few studies have analyzed this relationship. In particular, Baltas et al. (2017) have analyzed the effect of cost

TABLE 1.8: Results of SYS-GMM estimation.

Dependent variable	(1) *Cat fat*	(2) *Cat nonfat*
Independent variables		
$Cat\ fat_{t-1}$	0.905***(0.030)	
$Cat\ nonfat_{t-1}$		0.874***(0.015)
TE	0.147***(0.050)	0.085**(0.034)
$Size$	0.056***(0.014)	0.029***(0.008)
Cap	-0.004***(0.001)	-0.002**(0.001)
GDP	0.003***(0.001)	0.000(0.001)
$Intercept$	-0.29***(0.109)	-0.114*(0.064)
Country Dummies	Yes	Yes
Year Dummies	Yes	Yes
Number of instruments	52	52
Serial correlation test		
AR(1)	-7.26(*0.000*)	-8.84(*0.000*)
AR(2)	-0.15(*0.883*)	-0.17(*0.864*)
Hansen test	11.00(*0.963*)	16.18(*0.759*)

Number of observations: 8,800. (1) is referred to the model with *Cat fat* liquidity creation measure, (2) is referred to the other one. Standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%. For serial correlation tests, results are presented while values in italics reported in parentheses are p–values.

TABLE 1.9: Results of SYS-GMM estimation by specialisation.

Dependent variable	(1) *Cat fat*	(2) *Cat fat*	(3) *Cat fat*	(4) *Cat nonfat*	(5) *Cat nonfat*	(6) *Cat nonfat*
Independent variables						
$Cat\,fat_{t-1}$	0.679^{***}(0.204)	1.007^{***}(0.075)	0.966^{***}(0.048)			
$Cat\,nonfat_{t-1}$				0.750^{***}(0.225)	1.042^{***}(0.066)	0.891^{***}(0.021)
TE	0.152^{*}(0.084)	0.161^{**}(0.076)	0.172^{***}(0.065)	0.070^{*}(0.041)	0.147^{**}(0.067)	0.062^{**}(0.031)
Size	0.038(0.037)	0.012(0.014)	-0.026^{***}(0.010)	0.026^{***}(0.006)	0.027^{**}(0.013)	-0.002(0.007)
Cap	0.002(0.004)	-0.001(0.001)	0.000(0.002)	-0.002(0.002)	0.000(0.001)	-0.001(0.001)
GDP	0.002(0.019)	-0.007(0.005)	-0.008^{**}(0.003)	0.006(0.008)	0.001(0.005)	-0.007^{***}(0.002)
Intercept	-0.182(0.262)	-0.232(0.158)	0.008(0.087)	0.006(0.125)	-0.313^{**}(0.141)	-0.010(0.064)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of instruments	51	29	30	51	29	30
Serial correlation test						
AR(1)	-3.09(*0.002*)	-2.95(*0.003*)	-3.73(*0.000*)	-2.70(*0.007*)	-5.68(*0.000*)	-4.29(*0.000*)
AR(2)	-0.64(*0.525*)	0.38(*0.705*)	0.95(*0.341*)	-0.72(*0.474*)	-0.07(*0.944*)	0.76(*0.446*)
Hansen test	10.43(*0.960*)	1.17(*0.999*)	7.09(*0.852*)	27.14(*0.131*)	2.75(*0.973*)	13.07(*0.364*)
Number of observations	1,000	2,752	5,048	1,000	2,752	5,048

Models (1) and (4) are referred to commercial banks, models (2) and (5) are referred savings bank, models (3) and (6) are referred to cooperative banks. Standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%. For serial correlation tests, results are presented while values in italics reported in parentheses are p–values.

efficiency on potential M&As in UK and Greece and they have found a positive and significant relationship on liquidity creation increasing. In the same vein, Duan et al. (2021) have applied two accounting based efficiency measures and demonstrated that both cost and profit efficiency positively affect banks' liquidity creation.

Liquidity creation serves as a conduit through which financial institutions extend credit to the economy. This paper uses the contemporary methodology of BSFA to verify the hypothesis that optimal management practices, proxied by technical efficiency, allow banks to augment their liquidity generation irrespective of the prevailing banking market structure. In the context of this paper, BSFA appears more suitable than the standard SFA counterpart because conventional stochastic frontier methods assume that all banks have equal production possibilities. The sample employed in this study comprises commercial, cooperative and savings banks, which employ different technologies. For this reason, BSFA has been employed to disentangle firm–specific efficiency from technological differences across banks (Tsionas, 2002). Conversely, regulatory measures affecting bank capital, such as Basel III, exert a moderating influence on banks' liquidity generation. These findings contribute to the ongoing discourse on the role of bank–specific factors versus external regulatory frameworks in shaping financial intermediation outcomes. The estimates have been carried out by the implementation of a dynamic SYS–GMM estimation, to avoid possible endogeneity concerns. The choice of the dynamic specification and the instruments have been confirmed by serial diagnostics tests.

The mechanism underlying the positive relationship between technical efficiency and liquidity creation can be interpreted through several complementary channels. First, efficient banks are likely to exhibit superior risk management practices, which allow them to better assess and absorb risks associated with illiquid asset holdings, thereby supporting higher liquidity transformation. Second, efficiency reduces operational and funding costs, freeing up resources that can be reallocated to credit provision and other liquidity–creating activities. Finally, technically efficient banks may possess a stronger ability to manage maturity transformation, effectively balancing the liquidity of their liabilities with the longer–term nature of their assets. Together, these mechanisms suggest that efficiency enhances not only profitability but also the capacity to channel funds into productive lending, strengthening the role of banks as key liquidity creators in the financial system.

By highlighting the significance of managerial efficiency in fostering liquidity creation, the study underscores the need for policies that promote operational excellence alongside capital adequacy standards. Furthermore, the interaction between internal capabilities and external constraints invites a broader inquiry into how banks can adapt to evolving regulatory landscapes without compromising their core function of credit facilitation. Empirical findings have been corroborated also by the implementation of the standard stochastic frontier model.

Additional research is warranted to determine whether the findings of the current study are applicable in developing countries with different degrees of bank efficiency or in developed countries with more financial market–oriented systems (e.g., the United States and Canada). Future research could also explore how technological innovation intersects with efficiency and regulation in influencing liquidity creation. This would deepen how traditional banks can remain resilient and effective in an increasingly dynamic financial ecosystem.

Chapter 2

Principles for Responsible Banking: the Effect of Sustainable Practices on Bank Efficiency

Abstract

This study examines the impact of adopting the Principles for Responsible Banking, a plan promoted by the United Nations Environment Programme Finance Initiative, on bank efficiency. Using a sample of commercial banks from the Euro Area over the period 2014–2023, the study employs a one–step Stochastic Frontier Analysis to analyze the impact of sustainable practices on both banks' technical and cost efficiency. The findings indicate that participation in these initiatives leads to an increase in bank technical efficiency, while the Net–Zero Banking Alliance, part of the Principles for Responsible Banking, does not influence cost–side bank efficiency. This suggests that implementing sustainable practices, aligning with the Sustainable Development Goals, helps banks to improve their resources utilization. On the other hand, joining the Net–Zero Banking Alliance does not help European banks to improve cost efficiency. The study implies that sustainable banking practices aligned with traditional banking activities play a crucial role for sustainable economic development, by improving bank performance. Furthermore, the results underscore the importance of integrating environmental objectives with banks' core strategies, suggesting that responsible banking practices not only bolster resource utilization but may also enhance long–term resilience. These findings have practical implications for policymakers and regulators seeking to encourage sustainable finance, as they highlight the nuanced impact of different environmental initiatives on banks' performance.

2.1 Introduction

The financial industry, particularly the banking sector, plays a critical role in global economic growth and stability. In this context, sustainability has become a crucial pillar in the financial sector as banks play a decisive role in driving economic development while also stewarding environmental and social impacts. The relevance of the topic for policymakers is confirmed by Dikau and Volz (2021), who showed that 70 of 135 central banks have a "direct" or "indirect" sustainability mandate. In recent years, the integration of sustainability and responsibility into banking practices has been markedly changed. This shift is strongly represented by the adoption of the Principles for Responsible Banking (PRB), which were launched by the United Nations Environment Programme Finance Initiative (UNEP–FI) in 2019 through a cooperation with founding banks. These principles have the scope to align the banking sector with the objectives of the Sustainable Development Goals (SDGs) and the Paris Agreement, fostering a more sustainable and inclusive global economy. Indeed, Avrampou et al. (2019) underscored limited, fragmented and largely discursive engagement with the SDGs among leading European banks, while Ziolo et al. (2021) highlighted the importance of sustainable finance and found a strong link between sustainable finance model and social, environmental and economic sustainability. In this wave, Feridun and Talay (2023) argued that European countries with a higher proportion of wholesale banks that are signatories to the PRB are further advanced in their progress towards achieving the SDGs.

The PRB represent an operational and strategic framework that naturally aligns with Environmental, Social and Governance (ESG) principles. Both aim for a banking model that is not solely focused on short–term profit, but also takes into account the long–term impact on the environmental and social context, as well as the importance of transparent and responsible governance. By integrating sustainability considerations–such as responsible lending, green financing, and transparent governance practices–banks not only mitigate risks associated with climate change and resource depletion but also position themselves to capitalize on emerging market opportunities in renewable energy, clean technology, and other sustainable industries. The critical role of sustainability in shaping banks' activity has been assessed by Scholtens and Klooster (2019), who established that higher sustainability scores of banks are significantly associated with lower default risk. Moreover, stakeholders, including investors, customers, and regulators, increasingly expect financial institutions to embody responsible corporate citizenship. Meeting these expectations not only bolsters a bank's reputation and secures long–term profitability but also fosters resilience in an ever–evolving global landscape. Through sustainable practices, banks can ensure they remain competitive, compliant, and indispensable in shaping a more equitable and environmentally sound future. These implications in the banking industry represent a crucial aspect for both researchers and practitioners.

The PRB represent one of the latest attempts to develop a common structure to help banks achieve sustainable goals. For instance, the Equator Principles (EPs) were among the first international frameworks established to address climate and environmental risks. These principles differ from the PRB as they focus on providing a standardized framework and baseline for financial institutions to identify, evaluate, and manage environmental and social risks specifically in project financing (EPA, 2020). On the other hand, the PRB are designed to align the broader banking sector with the objectives of the SDGs and the Paris Agreement. In contrast to the broader sustainable initiatives typically promoted by banks, involvement in the PRB specifically aligns banks with the SDGs and necessitates a more strategic allocation of resources to fulfill these commitments. Therefore, understanding the relationship between responsible banking and efficiency is pivotal for both policymakers and banking executives. For policymakers, the findings could inform the development of regulations and incentives that promote sustainable finance while maintaining strong bank performance. For banking executives, insights from this study could guide strategic decisions on integrating sustainable practices into core business activities while maintaining or improving efficiency.

Empirical analyses regarding PRB represent a significant gap in previous research. Nonetheless, Torre Olmo et al. (2021) attempted to empirically evaluate the impact of PRB on banks' profitability by analyzing a sample of banks from 48 countries up to 2019, the year in which the PRB were launched. For this reason, this paper aims to evaluate the impact of the PRB on bank efficiency–a robust measure of bank performance–by extending the analysis to the years following their adoption. By examining commercial banks operating in the Euro Area, this study seeks to identify the effects of adopting responsible banking practices on banks' technical and cost efficiency.

Despite the noble intentions behind the PRB, there remains a critical need to assess their practical impact on bank operations, which has not been highly discussed in prior literature. In particular, this study aims to evaluate the impact of PRB in terms of efficiency, by relying on the one–step Stochastic Frontier Analysis, which allows for the simultaneous estimation of the production and cost function with the adoption of PRB, which is a driver of technical and cost (in)efficiency. This is a key aspect concerning bank's activity: efficiency, indeed, is a key indicator of a bank's operational performance and competitiveness (Berger and Humphrey, 1997). Thus, the incorporation of responsible banking principles could potentially influence bank efficiency in different ways–either positively, by fostering long–term risk management and innovation, or negatively, by imposing additional compliance costs and operational complexities.

In summary, this paper endeavors to contribute to the growing body of literature on sustainable finance by providing a comprehensive evaluation of how the PRB influence bank efficiency. The remainder of this paper is organized as follows: Section 2.2 describes background literature, Section 2.3 data and the empirical strategy, Section 2.4 provides the empirical results and Section 2.5 concludes the study.

2.2 Background literature

2.2.1 United Nations Environment Programme Finance Initiative's Principles for Responsible Banking

The Principles for Responsible Banking, endorsed by the United Nations Environment Programme Finance Initiative, offer a unique framework to ensure that the strategies and practices of participating banks are in harmony with society's vision for the future, as outlined by the Sustainable Development Goals and the Paris Climate Agreement, making them the foremost sustainable banking system globally (UNEP-FI, 2022). The primary objective is to expedite a positive global transformation for the benefit of people and the planet. Through the PRB, the United Nations bring banks together to collaboratively create innovative guidance and pioneering tools in critical areas of sustainable finance. They gain insights from best practices shared by peers, scientists, and industry experts, and receive both personalized feedback and group evaluations as they progress in implementing sustainability measures. Additionally, the PRB encompasses the Net–Zero Banking Alliance (NZBA), a climate–focused initiative within this framework launched in 2021. However, participation in one initiative does not necessarily mean that a bank will participate in the other.

The PRB framework primarily consists of six principles aimed at advancing sustainable finance. Banks that sign on commit to incorporating these principles across all business sectors. Specifically, Principle 1 requires banks to align their business strategies with the SDGs, the Paris Agreement and pertinent national and regional frameworks. Principle 2 involves minimizing the negative impacts on people and the environment caused by banks' activities, products, and services, as well as establishing and publicly disclosing targets to achieve these objectives. Principle 3 is founded on engaging responsibly with clients and customers to enhance sustainable practices and promote shared prosperity. Principle 4 emphasizes engaging with stakeholders, while Principle 5 encourages effective governance and the development of a responsible banking culture. Lastly, Principle 6 primarily focuses on transparency and accountability. Additionally, signatory banks fulfill their commitments through a three–step process involving impact analysis, target setting, and reporting. For further details, see UNEP-FI (2022).

The NZBA is a coalition of globally recognized banks launched in 2021, currently committed to reaching net–zero greenhouse gas emissions by 2050 through their lending, investment, and capital market activities (UNEP-FI, 2025). By adhering to the NZBA's framework, guidance, and peer learning opportunities, members can set and achieve credible science–based net–zero targets by 2030 or earlier. The Glasgow Financial Alliance for Net Zero and the Climate Accelerator for United Nations Environment Programme Finance Initiative's PRB utilize the NZBA to enhance banks' focus on climate issues. All NZBA members have signed the Commitment Statement, agreeing to adhere to the reporting processes and target setting detailed in the Guidelines for Climate Target Setting for Banks. A bank's CEO must sign the Commitment Statement before the bank can join the NZBA. All banks that have signed the commitment are required to set targets for 2030 or sooner, and for 2050, with interim targets established every five years starting from 2030. They must annually publish both absolute emissions and emissions intensity, and take a comprehensive approach to the use of offsets in their transition plans. The Guidelines for Climate Target Setting for Banks essentially outline four key principles: banks must set and publicly disclose both long–term and intermediate targets to align with the Paris Agreement's temperature goals, establish an emissions baseline, and annually report the emissions profile of their lending and investment activities. They should use widely recognized science–based decarbonization scenarios when setting these targets and regularly review them to ensure they remain consistent with current climate science. For additional information, refer to UNEP-FI (2025).

2.2.2 Sustainable banking

The existing body of literature has explored various aspects related to impact of sustainability, Environmental, Social and Governance practices and Corporate Social Responsibility (CSR) in the banking sector, related mainly to bank performance, and with mixed findings.

For what regards corporate governance, only gender–balanced boards positively affect banks' performance for sustainability, with leader gender diversity representing an important driver of environmental sustainability (Birindelli et al., 2018; Birindelli et al., 2019). In this wave, García-Sánchez et al. (2018) showed that banks with more independent directors and more female members on their boards incline toward socially responsible behavior, whereas Galletta et al. (2022) have discussed how increasing the proportion of female directors improves environmental and financial performance. However, according to Di Tommaso and Thornton (2020), high ESG scores are associated with a low reduction in risk–taking for banks that are high or low–risk takers, depending also on executive board characteristics.

Buallay (2019) analyzed how ESG disclosures affect European banks performance and showed a significant positive overall effect of ESG on the performance, captured by ROA, ROE and Tobin's Q. However, if considered individually, the environmental disclosure positively affects ROA and Tobin's Q, the CSR disclosure negatively affects all the performance profiles considered, while the corporate governance disclosure negatively affects ROA and ROE, and positively affects Tobin's Q. Miralles-Quirós et al. (2019a) extended these findings by demonstrating a positive and significant relationship of bank's environmental and corporate governance performance with Tobin's Q and with shareholder value creation. They found also a negative and significant correlation of bank's social performance with shareholder value creation. Brogi and Lagasio (2019) analyzed a panel of U.S. listed companies and provided evidence about a positive association between banks' ESG activities and their level of profitability, referring in particular to environmental dimension. By comparing manufacturing and banking sectors, Buallay (2020) showed that ESG reporting negatively affects the operational, financial and market performance in the banking sector, while the effects in the manufacturing one are positive. As far as the effects of ESG activities in emerging countries are concerned, Azmi et al. (2021) demonstrated that low levels of ESG activities positively influence bank value while, on the other hand, high levels of ESG activities lead to reducing returns to scale. Moreover, ESG activities positively affect bank value through the cost of equity, cash flow and the net interest margin. Furthermore, an increase in the ESG activity does not decrease the default risk of banks. Shakil et al. (2019) found a positive relationship of bank's environmental and social performance with emerging market banks financial performance.

Regarding investors' sentiment, Bătae et al. (2021) suggested that a bank's involvement in social responsibility initiatives and the adoption of best governance practices which could reduce the riskiness of its portfolio are not valued by market investors. Analyzing the news effect on stock performance, banks' stocks are significantly affected by negative ESG controversies media coverage (Wong and Zhang, 2022). Miralles-Quirós et al. (2019b) provided evidence that environmental and governance performance are positively and significantly related to bank's share prices, while social performance is negatively and significantly related to them. In this wave, Chiaramonte et al. (2022) showed that European banks fragility is mitigated by high ESG ratings. They extended their findings by showing that in common law countries ESG performance presents a greater relevance.

As far as the credit channel is concerned, Houston and Shan (2022) observed that banks are more likely to grant loans to borrowers with ESG profiles similar to their own and positively influence the borrower's subsequent ESG performance. In this vein, Liu et al. (2023) argued that banks' ESG ratings are negatively associated with their nonperforming loans, whereas Danisman and Tarazi (2024) showed how during periods of crisis, banks with higher ESG scores experience a smaller decline in lending activity. On the other hand, Galan and Tan (2024) analyzed a sample of Chinese banks and found that green credit negatively affects bank efficiency, with small and low capitalized banks which are more affected than the banks with high levels of risk.

Forgione et al. (2020) showed that CSR activities have a negative impact on bank efficiency, but in common law countries and in countries where the effectiveness of stakeholder protection is high, these activities improve bank efficiency. These findings are supported by Belasri et al. (2020), who found that CSR positively influences bank efficiency only in developed countries, in nations with strong investor protection, and in those with a high degree of stakeholder orientation. López-Penabad et al. (2023) analyzed the effect of Corporate Social Performance (CSP) on European banks and found evidence of a U–shaped relationship between CSP and bank efficiency. Furthermore, ESG investment is beneficial to bank efficiency (Cao et al., 2024). Additionally, Algeri et al. (2025) have integrated ESG factors in banks' cost efficiency frontiers, showing that stronger commitment to ESG leads to higher cost efficiency in the long term.

While previous studies have extensively analyzed the impact of ESG, CRS and CSP activities on bank efficiency and profitability, the specific influence of adherence to the PRB has not been widely explored. Unlike broader ESG, CRS, and CSP initiatives, involvement in the PRB directly aligns banks with the SDGs, requiring a more deliberate and strategic allocation of resources to achieve these commitments. The study by Torre Olmo et al. (2021) is among the first to empirically evaluate the impact of PRB on banks' profitability. In particular, they show that joining the PRB leads to an improvement in the performance. However, their study analyzes a time span between 2015 and 2019, which is the year when the PRB were launched. Therefore, this work aims to evaluate the effects of banks' commitment to specific responsible banking frameworks on efficiency, focusing on both the PRB and the NZBA. In particular, the study addresses the following research questions:

- RQ1: Does adherence to the Principles for Responsible Banking significantly improve banks' efficiency?
- RQ2: Does participation in the Net–Zero Banking Alliance lead to higher efficiency compared to non–participating banks?

By examining these questions, the analysis seeks to bridge the existing gap in the literature and provide a more nuanced understanding of how different sustainability frameworks influence banks' financial and operational performance.

2.3 Data and methodology

The analysis in this paper is based on a panel of 245 commercial banks from countries belonging to the Euro Area over the period 2014–2023. Data are obtained from Orbis Bank Focus and refer to consolidate accounts, including both no unconsolidated and unconsolidated companion accounts. The sample selection is based on the availability of information required to estimate

TABLE 2.1: Sample distribution by country.

Country	Commercial banks	Country	Commercial banks
Austria	16	Italy	30
Belgium	11	Latvia	9
Croatia	7	Lithuania	3
Cyprus	9	Luxembourg	8
Estonia	7	Malta	5
Finland	10	Netherlands	13
France	30	Slovakia	6
Germany	20	Slovenia	7
Greece	7	Spain	27
Ireland	9	Portugal	11

TABLE 2.2: Signatory and non–signatory banks.

	Signatories	Non–signatories
Principles for Responsible Banking	119	126
Net–Zero Banking Alliance	85	160

banks' efficiency scores. Specifically, banks are included if efficiency can be estimated within the observation period. This approach allows the inclusion of a broader and more representative set of banks while maintaining the robustness of the efficiency estimates. Information on banks' participation in the Principles for Responsible Banking and the Net–Zero Banking Alliance is retrieved from the official membership lists. The sample is described by country in Table 2.1, while Table 2.2 shows the number of signatory and non–signatory banks for PRB and NZBA.
In this paper technical and cost efficiency are estimated by using Stochastic Frontier Analysis, a parametric technique based on the premise that economic agents can not exceed the ideal frontier, and any deviations imply individual inefficiencies (Belotti et al., 2013). This study estimates the impact of PRB and NZBA on technical and cost efficiency by employing a "true" random effects model, which distinguishes between time–varying efficiency and firm–specific, time–invariant heterogeneity (Greene, 2005). The output is given as follows:

$$y_{it} = \alpha + \mathrm{x}'_{it}\beta + v_{it} - S\upsilon_{it} + \omega_i \tag{2.1}$$

where α is the constant, x' is a vector of explicative variables and β are the relative parameters. The error term is the sum of the common white noise term

(ν_{it}), distributed with zero mean and homoskedastic standard deviation, and the inefficiency is defined as the deviation from the maximum output achievable given the inputs (v_{it}). The sign of the inefficiency term, S, depends on whether the frontier describes production (+1) or cost (-1) functions. v_{it} has to conform to a half–normal distribution (a normal–half–normal distribution). The time invariant term (ω_i) allows the observation of cross firm heterogeneity. The normalized stochastic production function is assumed to be trans–logarithmic, as follows:

$$\ln Q_{it} = \eta_{+} \sum_{k=1}^{3} \xi_k lnP_{kit} + \frac{1}{2} \sum_{k=1}^{3} \sum_{j=1}^{3} \varrho_{kj} lnP_{kit} lnP_{jit} + (\nu_{it} - v_{it}) + \omega_i \tag{2.2}$$

where Q_{it} represents the output proxied by total assets. P_1, P_2 and P_3 are the three inputs: P_1 is the labor cost and it is calculated as the ratio between staff expense and total assets. P_2 is the physical capital price and it is obtained by dividing the sum of other administrative expenses and other operating expenses over fixed assets. P_3 is the borrowed funds price and it is obtained as the ratio between total interest expense and total liabilities. The normalized stochastic cost function is assumed to be trans–logarithmic as follows:

$$\begin{aligned} \ln C_{it} =& \eta_0 + \eta_1 \ln Q_{it} + \frac{1}{2}\eta_2 \ln Q_{it}^2 + \sum_{k=1}^{3} \xi_k lnP_{kit} + \frac{1}{2} \sum_{k=1}^{3} \sum_{j=1}^{3} \rho_{kj} lnP_{kit} lnP_{jit} \\ &+ \frac{1}{2} \sum_{k=1}^{3} \varrho_k lnQ_{it} lnP_{kit} + (\nu_{it} + v_{it}) + \omega_i \end{aligned} \tag{2.3}$$

where C_{it} is the total cost represented by the total operating expense, while the output and input variables are the same as the production function (Algeri et al., 2022). To sum up, the PRB and the NZBA determine the efficiency variance function (σ_{uit}). However, due to the fact that joining the NZBA does not necessarily require the participation in PRB, both initiatives are analyzed in influencing bank efficiency. The PRB and $NZBA$ are dummy variables which take 1 if in that year the bank was part of the initiative, 0 otherwise. The estimation of the production and cost frontier, and the efficiency determinant coefficient are carried out simultaneously by applying the one–step approach which follows Battese and Coelli (1995). This approach has not the bias of the alternative two–stage method (Schmidt, 2011). The inefficiency equation includes the PRB and NZBA variables, with a set of control variables commonly used in studying bank efficiency (Pasiouras, 2008; Pasiouras

TABLE 2.3: Variables definition.

Variable	Definition
Total Assets	Bank's total assets, winsorized at 1% level.
Total Operating Expense	Bank's total operating expense, winsorized at 1% level.
Labor Cost	Staff expense/total assets, winsorized at 1% level.
Physical Capital Price	(Other administrative expense+other operating expense)/fixed assets, winsorized at 1% level.
Borrowed Funds Price	Total interest expense/total liabilities, winsorized at 1% level.
PRB	Participation in the Principles for Responsible Banking
NZBA	Participation in the Net–Zero Banking Alliance
GDP	Annual percentage growth rate of GDP (2015=100), winsorized at 1% level.
Inflation	Annual growth rate of the GDP implicit deflator, winsorized at 1% level.
Concentration	Herfindahl–Hirschman index calculated on banks' total assets, winsorized at 1% level.

Macroeconomic variables are obtained from the World Development Indicators (World Bank).

TABLE 2.4: Summary statistics.

Variable	Minimum	Maximum	Mean	Standard deviation
Total Assets	109,123	1,595,835,000	104,000,000	268,000,000
Total Operating Expense	4,800.73	25,850,000	1,509,999	3,964,207
Labor Cost	0.159	6.323	1.093	0.920
Physical Capital Price	19.456	10913.790	488.152	1352.993
Borrowed Funds Price	0.040	5.534	0.977	0.997
GDP	-10.940	12.972	2.079	3.841
Inflation	-1.338	10.050	2.352	2.188
Concentration	0.178	0.874	0.294	0.120

Accounting data are expressed in thousand Euros.

et al., 2009b; Mutarindwa et al., 2021).

$$u_{it} = f(PRB_{it}, NZBA_{it}, GDP_{it}, Inflation_{it}, Concentration_{it}) \tag{2.4}$$

Specifically, in the specification two macro variables have been included (i.e. *GDP* and *Inflation*). The first one is defined as the annual percentage growth rate of GDP at marked prices based on constant local currency, while the *Inflation* is measured by the annual growth rate of the GDP implicit deflator. The *Concentration* variable is the Herfindahl–Hirschman index, which represents the total assets concentration index by country and by year.

Table 2.3 provides the definitions of all variables employed in this study, while the summary statistics are reported in Table 2.4.

2.4 Empirical results

The empirical results reported in Table 2.5 show the impact of the Principles for Responsible Banking and the Net–Zero Banking Alliance on banks' technical inefficiency. The findings indicate a negative and significant impact on bank technical inefficiency in both specifications at 1% level. This means that joining the PRB leads banks to improve their technical efficiency. Furthermore, the analysis shows adhering to the NZBA leads banks to a statistically significant reduction in their levels of inefficiencies in years when they comply with the NZBA. This suggests that the commitment to aligning lending and investment portfolios with net–zero greenhouse gas emissions may encourage better resource allocation, enhanced risk assessment of environmentally sensitive activities, and more innovative lending practices. By directing capital towards projects and sectors that are resilient in the face of environmental and regulatory changes, NZBA–member banks appear to streamline their operations, reduce inefficiencies, and improve the quality of their output. On the other hand, the *Concentration* index appears statistically significant in rising European bank's technical inefficiency.

The economic magnitude of sustainable–finance commitments is sizeable: on average, PRB participation leads to an increase of 28.6 percentage points in technical efficiency, while participation in the NZBA leads to a 24.1 percentage–point advantage. These gaps indicate economically meaningful differences in productive efficiency, implying that signatory banks are able to generate higher output for a given level of inputs–or, equivalently, achieve the same output using fewer resources.

Subsequently, the cost function has been analyzed. Results reported in Table 2.6 show even in this case a negative sign on the coefficient related to the impact of PRB on banks' cost inefficiency. This implies that banks which adopt the PRB show a rise in their levels of cost efficiency in the years they were part of the programme. The analysis reveals a positive and statistically significant relationship between the adoption of the PRB and both technical and cost efficiency within the banking sector. Specifically, banks adhering to PRB standards tend to utilize their resources more effectively, streamline internal processes, and manage risks in a way that reduces unnecessary expenses and operational bottlenecks. These results suggest that integrating sustainability considerations into the core strategy and governance structures of financial institutions does not solely serve ethical or reputational purposes; it also fosters genuine operational benefits. Beyond improving cost control, the association with technical efficiency indicates that responsible banking practices may enhance the overall quality and productivity of a bank's operations. By better assessing borrower risk, anticipating environmental and social challenges, and adopting more resilient operational

TABLE 2.5: One–step stochastic frontier estimates for production function.

	(1)	(2)	(3)
$\ln P_1$	-0.662***(0.070)	-0.685***(0.077)	-0.705***(0.052)
$\ln P_2$	-0.078***(0.025)	-0.073***(0.015)	-0.060**(0.025)
$\ln P_3$	0.099***(0.018)	0.096***(0.020)	0.093***(0.025)
$1/2 \times \ln P_1 \times \ln P_2$	0.031(0.068)	0.008(0.037)	-0.001(0.038)
$1/2 \times \ln P_1 \times \ln P_3$	0.126(0.084)	0.108*(0.060)	0.091*(0.048)
$1/2 \times \ln P_2 \times \ln P_3$	0.018(0.016)	0.014(0.016)	0.025(0.017)
$1/2 \times (\ln P_1)^2$	-0.161(0.103)	-0.153(0.116)	-0.202***(0.068)
$1/2 \times (\ln P_2)^2$	-0.024(0.025)	-0.016(0.015)	-0.017(0.020)
$1/2 \times (\ln P_3)^2$	0.063***(0.017)	0.048***(0.013)	0.046***(0.012)
$Intercept$	16.816***(0.092)	16.548***(0.039)	16.488***(0.083)
σ_v			
PRB		-1.005***(0.333)	
$NZBA$			-0.781***(0.252)
GDP		-0.009(0.014)	0.002(0.015)
$Inflation$		-0.113**(0.053)	-0.138***(0.048)
$Concentration$		3.662**(1.848)	3.665**(1.704)
$Intercept$		-2.484***(0.564)	-2.419***(0.654)
$E(\sigma_v)$		0.407	0.437
σ_v		0.088***(0.029)	0.062(0.074)

Number of observations: 1,922. Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

models, PRB–compliant banks can achieve stronger, more sustainable performance outcomes. In effect, the alignment with PRB encourages a forward–looking approach to risk and resource allocation, ultimately contributing to a more stable and efficient banking environment.

Results referred to the analysis of banks that joined the NZBA, show that the participation in this sustainable program does not have a statistically significant impact on cost–side banks efficiency. This finding suggests that while the alliance's climate–related guidelines and targets help sharpen technical capabilities and raise operational standards, the direct effect on cost structures may not be immediate or straightforward. Initial investments in training, new technologies, and data management tools necessary to meet NZBA commitments may not yet translate into measurable cost savings. Additionally, cost efficiency may depend on a wider set of factors, including a bank's pre–existing business model, market conditions, and the time frame over which benefits are realized.

With respect to cost efficiency, PRB participation displays a moderate improvement of about 4.2 percentage points. Participation in the NZBA shows a similar average efficiency advantage of 4.3 percentage points, although the coefficient is not statistically significant. Given the limited number of NZBA signatories and the relatively short period since the initiative's launch, this lack of significance is likely to reflect the early stage of implementation and limited data coverage, rather than the absence of an economic effect. Overall, the results suggest that sustainable–finance commitments are associated with slightly higher cost efficiency, but their measurable impact may take time to materialize.

To further assess the relationship between PRB and NZBA participation and bank efficiency, an analysis by bank size has been conducted. Specifically, the sample was divided into small and large banks according to the significance criterion established by the European Central Bank, which classifies a bank as significant when the total value of its assets exceeds €30 billion. The results of this empirical analysis are presented in Table 2.7 and Table 2.8.

The analysis conducted by size confirms the empirical findings that participation in the PRB is systematically associated with higher levels of both technical and cost efficiency, whereas NZBA participation contributes to efficiency improvements only on the technical side.

To validate the robustness of the results, a two–stage Data Envelopment Analysis (DEA) (Simar and Wilson, 2007) was performed employing the same

TABLE 2.6: One–step stochastic frontier estimates for cost function.

	(1)	(2)	(3)
$\ln Q$	0.970***(0.021)	0.964***(0.035)	0.914***(0.029)
$\ln P_1$	0.944***(0.072)	0.917***(0.083)	0.924***(0.083)
$\ln P_2$	0.071**(0.033)	0.059(0.039)	0.062(0.044)
$\ln P_3$	-0.021(0.019)	-0.027(0.018)	-0.027(0.019)
$1/2 \times \ln Q \times \ln P_1$	0.120***(0.045)	0.106*(0.054)	0.107*(0.061)
$1/2 \times \ln Q \times \ln P_2$	0.030*(0.016)	0.024(0.019)	0.026(0.021)
$1/2 \times \ln Q \times \ln P_3$	-0.011(0.011)	-0.011(0.013)	-0.011(0.011)
$1/2 \times \ln P_1 \times \ln P_2$	-0.029(0.041)	-0.031(0.044)	-0.032(0.045)
$1/2 \times \ln P_1 \times \ln P_3$	-0.132**(0.065)	-0.121(0.089)	-0.119*(0.070)
$1/2 \times \ln P_2 \times \ln P_3$	-0.007(0.015)	-0.005(0.014)	-0.008(0.016)
$1/2 \times (\ln Q)^2$	0.004(0.008)	0.005(0.012)	-0.007(0.011)
$1/2 \times (\ln P_1)^2$	0.176**(0.082)	0.160*(0.092)	0.170*(0.100)
$1/2 \times (\ln P_2)^2$	-0.028**(0.012)	-0.027**(0.010)	-0.025**(0.011)
$1/2 \times (\ln P_3)^2$	-0.002(0.013)	-0.006(0.014)	-0.006(0.015)
$Intercept$	14.743***(0.065)	14.714***(0.077)	14.602***(0.118)
σ_v			
PRB		-0.769***(0.259)	
$NZBA$			-0.438(0.372)
GDP		0.013(0.010)	0.020**(0.010)
$Inflation$		0.111**(0.044)	0.097**(0.044)
$Concentration$		1.436(0.525)	1.162(2.189)
$Intercept$		-3.759***(0.711)	-3.792***(0.609)
$E(\sigma_v)$		0.205	0.202
σ_v		0.088**(0.040)	0.091***(0.030)

Number of observations: 1,922. Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

TABLE 2.7: One–step stochastic frontier estimates for production function by size.

	(1)	(2)	(3)	(4)
$\ln P_1$	-0.694***(0.037)	-0.672***(0.153)	-0.297(0.182)	-0.333(0.202)
$\ln P_2$	-0.060***(0.012)	-0.047**(0.020)	-0.096(0.076)	-0.087(0.073)
$\ln P_3$	0.127***(0.022)	0.121***(0.043)	-0.047(0.042)	-0.037(0.047)
$1/2 \times \ln P_1 \times \ln P_2$	-0.038(0.038)	0.020(0.083)	-0.039(0.124)	0.024(0.119)
$1/2 \times \ln P_1 \times \ln P_3$	0.038(0.053)	0.058(0.222)	-0.049(0.103)	-0.022(0.136)
$1/2 \times \ln P_2 \times \ln P_3$	0.022(0.015)	0.009(0.020)	-0.082***(0.031)	-0.062*(0.032)
$1/2 \times (\ln P_1)^2$	-0.239***(0.085)	-0.270(0.178)	0.378*(0.209)	0.297(0.214)
$1/2 \times (\ln P_2)^2$	-0.015(0.011)	-0.031**(0.014)	-0.047(0.035)	-0.041(0.037)
$1/2 \times (\ln P_3)^2$	0.066***(0.017)	0.065(0.053)	0.031(0.020)	0.025(0.027)
$Intercept$	15.259***(0.049)	15.090***(0.036)	18.405***(0.103)	18.596***(0.109)
σ_υ				
PRB	-0.995***(0.359)		-3.932***(1.469)	
$NZBA$		-0.638*(0.357)		-28.789***(5.665)
GDP	0.013(0.016)	0.017(0.016)	-0.059(0.047)	0.004(0.031)
$Inflation$	-0.143***(0.048)	-0.161***(0.060)	-1.137**(0.492)	-0.958**(0.438)
$Concentration$	1.739(1.726)	1.806(1.706)	-12.838(10.095)	-11.902(10.346)
$Intercept$	-1.593***(0.583)	-1.617***(0.598)	0.461(2.716)	-0.399(2.290)
$E(\sigma_\upsilon)$	0.489	0.497	0.081	0.081
σ_ν	0.050*(0.027)	0.027(0.037)	0.123***(0.012)	0.128***(0.011)
Number of observations	1,274	1,274	648	648

Robust standard errors are reported in parentheses. Models (1) and (2) refer to small banks, (3) and (4) refer to large banks. ***, ** and * represent respectively significance at 1%, 5% and 10%.

TABLE 2.8: One–step stochastic frontier estimates for cost function by size.

	(1)	(2)	(3)	(4)
$\ln Q$	1.042***(0.071)	0.936***(0.317)	1.011***(0.040)	0.951***(0.184)
$\ln P_1$	1.066***(0.107)	1.025***(0.212)	0.570***(0.077)	0.509***(0.126)
$\ln P_2$	0.079(0.051)	0.068(0.106)	-0.030(0.034)	-0.046(0.039)
$\ln P_3$	-0.041(0.033)	-0.057(0.036)	-0.057**(0.026)	-0.085(0.057)
$1/2 \times \ln Q \times \ln P_1$	0.154***(0.052)	0.133(0.087)	0.053(0.125)	0.029(0.099)
$1/2 \times \ln Q \times \ln P_2$	0.027(0.023)	0.021(0.037)	-0.032(0.025)	-0.022(0.050)
$1/2 \times \ln Q \times \ln P_3$	-0.012(0.017)	-0.022(0.019)	-0.004(0.010)	-0.010(0.031)
$1/2 \times \ln P_1 \times \ln P_2$	-0.064(0.040)	-0.076(0.059)	-0.112(0.069)	-0.134(0.087)
$1/2 \times \ln P_1 \times \ln P_3$	-0.030(0.036)	-0.037(0.048)	-0.138***(0.038)	-0.190***(0.038)
$1/2 \times \ln P_2 \times \ln P_3$	-0.002(0.013)	-0.003(0.016)	-0.031(0.026)	-0.059(0.077)
$1/2 \times (\ln Q)^2$	0.019(0.018)	-0.006(0.081)	-0.018(0.021)	-0.083(0.097)
$1/2 \times (\ln P_1)^2$	0.214***(0.078)	0.193(0.145)	-0.153(0.120)	-0.162*(0.094)
$1/2 \times (\ln P_2)^2$	-0.031**(0.013)	-0.028**(0.014)	-0.104***(0.019)	-0.114***(0.040)
$1/2 \times (\ln P_3)^2$	-0.009(0.012)	-0.009(0.013)	-0.006(0.009)	-0.008(0.012)
$Intercept$	14.814***(0.143)	14.588***(0.394)	14.506***(0.058)	14.273***(0.072)
σ_v				
PRB	-0.701**(0.293)		-1.210***(0.305)	
$NZBA$		-0.604(0.387)		-0.202(0.436)
GDP	0.014(0.011)	0.016(0.012)	0.009(0.017)	0.015(0.017)
$Inflation$	0.115***(0.032)	0.118***(0.034)	0.022(0.073)	-0.057(0.084)
$Concentration$	-1.152(1.621)	-1.672(1.727)	-21.603***(7.549)	-18.189**(7.040)
$Intercept$	-2.640***(0.563)	-2.375***(0.585)	1.402(1.709)	0.448(1.577)
$E(\sigma_v)$	0.255	0.277	0.135	0.136
σ_V	0.047***(0.015)	0.041**(0.020)	0.058***(0.006)	0.060***(0.008)
Number of observations	1,274	1,274	648	648

Robust standard errors are reported in parentheses. Models (1) and (2) refer to small banks, (3) and (4) refer to large banks. ***, ** and * represent respectively significance at 1%, 5% and 10%.

output and inputs included in the SFA specification. The empirical findings confirm the positive impact that both initiatives have on bank efficiency. The DEA estimation results are reported in Appendix B.

The divergence between the effects of PRB and NZBA on cost efficiency may reflect differences in the nature, timing, and implementation of these initiatives. First, while the PRB framework primarily emphasizes governance, strategy integration, and stakeholder engagement–areas that can quickly translate into improved managerial practices and cost control–the NZBA involves more demanding and capital–intensive commitments. Achieving net–zero alignment typically requires investments in new data infrastructures, climate–risk assessment systems, and portfolio rebalancing toward low–carbon assets, all of which entail significant upfront costs. Consequently, such expenditures may temporarily offset potential cost savings. Second, the NZBA is a more recent initiative (launched in 2021), and its cost impacts may not yet be observable within the study period. Cost efficiency gains are likely to materialize only in the medium to long term as banks internalize learning effects, standardize reporting procedures, and benefit from technological diffusion. Finally, the distinction between technical and cost efficiency may also play a role: technical efficiency captures improvements in operational processes and productive capabilities, whereas cost efficiency also depends on input price dynamics and market conditions. Hence, NZBA membership may already enhance banks' operational performance without yet reducing the relative cost of inputs. Over time, as transition investments mature and economies of scale emerge, a stronger alignment between technical and cost efficiencies could be expected.

It is possible to observe that the participation in sustainable programmes presents an overall statistically significant effect on reducing European banks inefficiencies. Anyway, adopting the practices implemented by the NZBA does not help banks to reduce their cost inefficiencies. In essence, the NZBA appears to foster technical efficiency improvements, likely through enhanced strategic positioning and more focused operational processes, but does not demonstrate a clear–cut advantage in reducing overall costs. These results highlight the potential for environmental and climate–related initiatives to shape operational practices without necessarily delivering immediate financial efficiencies. Over a long horizon, however, such initiatives may still yield cost–related benefits as bank gain experience, scale their sustainability measures, and integrate climate considerations more thoroughly into their core business models.

2.5 Concluding remarks

The attention to sustainability goals has always been an important topic for researchers, practitioners and policymakers alike, as these goals are crucial for mitigating climate change and improving governance and social conditions. In recent years, banks have increasingly focused on these issues. In 2019 the United Nations proposed adopting the Principles for Responsible Banking to regulate Environmental, Social and Governance disclosure for banks. The aim of this study was to understand and empirically evaluate whether the adoption of these principles aligns with banks' activities.

While numerous studies have examined the impact of ESG, Corporate Social Responsibility and Corporate Social Performance, none have specifically analyzed the PRB, which requires higher investments and different requirements to align with the Paris Agreement and Sustainable Development Goals. Torre Olmo et al. (2021) were the first to explore whether the PRB improve banks' performance, but their sample did not consider the effect in the years following the start of participation in this program and the adoption of compliant practices.

To address this gap, this analysis, using the Stochastic Frontier Analysis to observe whether the adoption of the PRB led to improvements in banks' technical and cost efficiency, have been conducted by relying on trans–logarithmic functions. Empirical results demonstrate that banks adopting the principles experience a statistically significant improvement in their efficiency scores. In particular, technical efficiency scores increase significantly when banks adopt PRB and join the Net–Zero Banking Alliance. Additionally, the adoption of the PRB is related to an increase in the cost efficiency scores. For what regards the relationship between the cost–side efficiency and the NZBA participation, no statistically significant effect has been observed. This divergence between the impacts of PRB and NZBA can be interpreted in light of their different scope and maturity. While PRB participation primarily promotes governance alignment and strategic integration–elements that can rapidly translate into both operational and cost improvements–the NZBA requires substantial upfront investments in data systems, portfolio adjustments, and climate–risk assessment tools. The limited number of signatories and the initiative's recent inception in 2021–together with the substantial upfront investments required–may delay observable cost gains. Moreover, since technical efficiency captures improvements in productive capacity rather than input price effects, NZBA banks may already operate more efficiently without yet achieving measurable cost savings. Over time, however, these initial investments could translate into stronger cost performance as transition measures become embedded in routine operations.

These findings suggest that participation in the PRB enhances banks' technical and cost efficiency. Engaging with the PRB may lead to improved compliance, reporting, and strategic realignment that optimize operational processes and reduce costs. The implications of these results suggest that policymakers should encourage initiatives like the PRB that align ESG goals with the enhancement of banks' efficiency. Integrating environmental and social practices not only requires effort from banks but also yields efficiency gains, making it crucial to find ways to merge banks' activities with sustainability and green practices. The findings indicate that banks and policymakers can successfully balance the pursuit of sustainability objectives with maintaining and even improving efficiency. Banks might leverage support mechanisms within the PRB to manage and reduce operational costs effectively. Both sustainability and efficiency are pivotal in determining appropriate economic and social development. For this reason, promoting a suitable framework like the PRB could represent one of the first steps required to foster sustainable economic growth. Taken together, these findings underscore the potential for responsible banking initiatives to simultaneously advance both societal good and business efficiency. They indicate that, rather than representing a trade–off between sustainability and profitability, the adoption of PRB may enhance the competitive positioning, financial resilience, and long–term value generation of banks.

The limitations of this study are mainly related to the sample, as only commercial European banks have been considered, and the time span since the PRB were launched in 2019 (NZBA was even launched in 2021). Future research could focus on extending the sample to include banks from other regions, particularly those in common law and developing countries, and on extending the time span to observe if, in the long run, joining the PRB and/or the NZBA, and potentially modifying their framework, might continue to improve not only social and environmental outcomes but also bank performance, thereby generating an overall positive effect on the economic system. These positive impacts on efficiency may diminish over time as banks streamline their processes ane the benefits of sustainable practices may be mitigated. Although PRB participation may increase efficiency in the short term, it is important to view this within the broader context of achieving the Sustainable Development Goals. The trade–off might be considered acceptable from a societal perspective if the long–term benefits in terms of technical and cost efficiency will be stable.

Chapter 3

Efficiency Under Siege: Organized Crime and the Efficiency of Cooperative Banks in Italy

Abstract

This study investigates the impact of organized crime on the efficiency of cooperative banks in Italy. Relying on a panel of cooperative credit banks observed over the period 2011–2019, the analysis applies a one–step Stochastic Frontier Analysis with trans–logarithmic specifications to estimate both technical and cost efficiency. The presence of organized crime is captured through a composite indicator developed at the provincial level. The findings show that cooperative banks operating in areas with a strong criminal presence experience significant reductions in both technical and cost efficiency. This evidence suggests that a hostile institutional and social environment represents a major obstacle to efficient banking operations, undermining governance structures and distorting cost dynamics. The results highlight the need to confront these challenges, which are particularly relevant for cooperative banks given their crucial role in supporting credit availability, local financing, and regional development. Overall, the study contributes to the literature by documenting a novel external determinant of bank inefficiency and by providing insights of practical relevance for policymakers and regulators. In particular, strengthening institutional safeguards and governance mechanisms may help mitigate the efficiency losses associated with the pervasive influence of criminal organizations.

3.1 Introduction

Cooperative banks play a distinctive and essential role in the financial systems of many countries, distinguished by their unique organizational structure, governance model, and value orientation. Unlike traditional commercial banks, cooperative banks prioritize mutual support among members, local community development, and social goals alongside financial performance. In Italy, cooperative banks–known as Banche di Credito Cooperativo (Credit Cooperative Banks, or CCBs)–have historically contributed to fostering local economic growth, particularly in regions underserved by larger financial institutions. Founded on principles of mutualism and democratic governance, CCBs operate under a one–member–one–vote system, ensuring that all members have equal influence regardless of their shareholding size, and maintaining a strong connection to local communities. These banks primarily serve small and medium–sized enterprises (SMEs), families, and individuals, offering tailored financial services that address specific local needs. Their deep–rooted community presence allows them to better understand and respond to regional economic and social dynamics.

This local embeddedness also translates into greater market power compared to commercial banks (Viola, 2024), particularly because loan rates tend to decrease with proximity between the borrower and the lending institution, given the importance of soft information, which is often locally sourced (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). In line with this, Williams and Gardener (2003) argue that local banks are especially suitable financing vehicles due to their specialized knowledge of regional market conditions and risks, and often exhibit high cost efficiency. Furthermore, CCBs have a significant impact on GDP per worker (Destefanis et al., 2014). Local financial development is especially important for small firms, which typically face greater difficulties in accessing credit, while greater local banking concentration has been shown to reduce the probability of bankruptcy for medium–sized firms (Arcuri and Levratto, 2020).

Italian CCBs possess specific legal and operational characteristics, as defined by the Testo Unico Bancario (Consolidated Law on Banking, TUB). Following the 2016 reform, CCBs were restructured as limited liability cooperative joint–stock companies and are required to join a cooperative banking group. The nominal value of each share must be no less than €25 and no more than €500. Each CCB must have at least 500 cooperative members, all of whom must reside or work within the geographical area in which the bank operates. Governance follows a one–member–one–vote principle, and no individual member may hold more than €100,000 in shares. CCBs are legally obliged to allocate at least 70% of their annual net profits to a legal reserve. Additionally, a portion of annual profits must be directed toward mutualistic funds that promote and support cooperative development, as mandated by law. Any remaining profits that are not used for the revaluation of shares, transferred to other reserves, or distributed among shareholders must be allocated to charitable or mutualistic purposes.

The inherently local nature of CCBs makes their operations deeply embedded in the socio–economic context of the territories in which they operate. While this local anchoring is often considered a strength–facilitating access to soft information and tailored lending–it also exposes CCBs to significant risks when the local environment is compromised by criminal networks. In areas affected by organized crime, local banks may become vulnerable to infiltration or manipulation, as criminal groups seek to exploit financial institutions for both profit–making and reputation–laundering purposes. These groups may attempt to channel illicit funds through local banks to legitimize illegal revenues, or infiltrate bank governance structures via complicit or coerced members. The democratic and decentralized governance model of CCBs, based on the one–member–one–vote rule and local membership criteria, can unintentionally create loopholes for criminal influence, especially in territories where social cohesion is weakened by clientelism, intimidation, or economic dependence on criminal organizations. In this context, cooperative banks may face heightened risks of money laundering, fraudulent loan applications, and distorted credit allocation, whereby funds are directed toward front companies or associates of criminal enterprises. This not only undermines the integrity of the financial system, but also erodes trust in legal economic actors, further discouraging legitimate investment.

Organized crime continues to pose structural challenges to Italy's socio–economic development and plays a central role in perpetuating regional disparities. For instance, Detotto and Otranto (2010) show that criminal activity operates as a tax on the economy, discouraging investment and reducing firms' competitiveness. Similarly, Pinotti (2015) finds that organized crime has contributed to a GDP *per capita* loss of nearly 16% in southern Italy. High crime levels also act as a deterrent to foreign direct investment, with Daniele and Marani (2011) showing that criminal presence signals an unfavorable socio–institutional environment to international investors. Mocetti and Rizzica (2024) emphasize that mafia activity exacerbates territorial inequalities, especially in southern provinces, and report that Italy ranks second in Europe in terms of the economic costs imposed by organized crime. Additionally, Fioroni et al. (2025) find that in high–crime areas, public expenditure has a negative impact on *per capita* GDP, further highlighting the long–term structural damage of criminal influence.

A large body of literature has examined the various determinants of bank efficiency. However, limited attention has been paid to the role of criminal dynamics. In a recent study, Agostino et al. (2023) analyze the impact of institutional quality–measured using the indicator developed by Nifo and Vecchione (2015)–on the cost efficiency of Italian CCBs, applying Stochastic Frontier Analysis. Their results suggest that stronger institutional frameworks are positively associated with improvements in bank cost efficiency, with control of corruption emerging as a particularly influential factor. Nevertheless, their analysis does not account for direct and objective measures of organized crime presence, thereby overlooking a critical dimension of the local institutional environment. To address this gap, the present work investigates the effect of a composite indicator of organized crime, constructed by Forgione et al. (2024) at the provincial level, on both technical and cost efficiency of CCBs. The findings reveal a statistically significant and negative impact of organized criminal networks on bank efficiency. This underscores the urgent need to strengthen law enforcement capacity and implement preventive mechanisms to shield financial institutions from criminal interference. The presence of organized crime not only distorts credit allocation and operational practices but also exacerbates socio–economic inequalities, representing a substantial obstacle to sustainable economic development at both the local and national levels.

In summary, this paper seeks to contribute to the existing body of literature by analyzing how the presence of criminal networks affects both the technical and cost efficiency of CCBs. The remainder of this paper is structured as follows: Section 3.2 reviews the relevant literature, Section 3.3 outlines the data and empirical strategy, Section 3.4 presents the empirical results and Section 3.5 concludes the study.

3.2 Background literature

3.2.1 Efficiency in cooperative banks

A substantial body of literature has examined various aspects of cooperative banks, with particular attention to their contribution to growth and financial stability. Empirical evidence suggests that cooperative banks exhibit greater stability than commercial banks, largely due to the lower volatility of their returns (Hesse and Čihák, 2007), and have played a positive role in enhancing the stability of European national financial systems (Groeneveld and Vries, 2009). The relationship between market structure and bank soundness has been widely debated. Fiordelisi and Mare (2014) find that bank market power negatively "Granger–causes" stability, implying a positive link between competition and soundness. Conversely, Clark et al. (2018) report a non–linear relationship, whereby market power–particularly in the loan market–can also enhance stability. At the same time, excessive internal competition among CCBs is considered a negative–sum game, and thus limiting it may help preserve the stability of cooperative banking networks (Coccorese and Ferri, 2019). Beyond stability, CCBs have been associated with stronger economic outcomes compared to conventional banks, fostering higher income, employment, and firm growth rates (Coccorese and Shaffer, 2021). Moreover, local banks continue to serve as difficult–to–replace lenders for SMEs (Hasan et al., 2021). These features suggest that cooperative banks, and particularly Italian CCBs, operate under structural and governance conditions that distinguish them from commercial banks. Their local focus, mutualistic objectives, and democratic ownership models not only affect their business orientation but also influence their efficiency patterns and responses to market and institutional environments.

The technical and cost efficiency of banks has long been a central topic in both managerial and policy debates. Higher efficiency levels are positively and significantly associated with the probability of survival of cooperative banks (Fiordelisi et al., 2011; Fiordelisi and Mare, 2013). In Italy, mutual cooperative banks have historically engaged in frequent mergers; however, Coccorese and Ferri (2020) find that only 5% of such operations have led to improvements in CCBs' cost efficiency. Efficiency gains have broader economic and social implications. For instance, improvements in cooperative banks' cost efficiency contribute to reducing the size of the underground economy (Barra et al., 2024a) and have a positive, significant impact on firms' process innovation (Barra and Ruggiero, 2022). Moreover, business models play a crucial role: retail–oriented cooperative banks tend to be more cost– and profit–efficient than those with a market–oriented approach (Ayadi et al., 2023). Finally, bank cost efficiency also helps reduce income inequality, with cooperative banks achieving the best results in this regard (Barra and D'Aniello, 2025).

A large body of literature has examined the influence of environmental conditions on banks' efficiency, yet no consensus has been reached on their effects. Some studies emphasize the relevance of local market conditions: Dietsch and Lozano-Vivas (2000) and Lozano-Vivas et al. (2002) identify them as key determinants of banks' efficiency, while others downplay their role (Bos and Kool, 2006; Burgstaller, 2020). For Italian cooperative banks, Battaglia et al. (2010) find that environmental conditions significantly affect efficiency estimates. More specifically, CCBs' efficiency tends to increase with market concentration and demand density, and to decrease as the number of bank branches grows; moreover, higher levels of local development can negatively impact cost efficiency (Aiello and Bonanno, 2016a; Aiello and Bonanno, 2016b). Consistently, Bernini and Brighi (2018) show that although efficient local banks boost the local economy, branch expansion may harm both banks' efficiency and local development. Institutional quality also emerges as a crucial factor. In China, Pasiouras et al. (2009a) demonstrate the importance of institutional variables in shaping banking efficiency. Cross–country studies reveal that higher institutional quality in the home country, as well as greater similarity between home and host country institutions, can reduce foreign bank efficiency (Lensink et al., 2008). However, Lensink and Meesters (2014) confirm that well–developed institutions support the efficient operation of commercial banks. In the Italian context, Agostino et al. (2023) analyze CCBs at the branch level, showing that better institutional quality–measured through the index by Nifo and Vecchione (2015)–is associated with improvements in cost efficiency. Moreover, Barra et al. (2024b) find that controlling corruption amplifies the positive effect of banks' cost efficiency on economic development. Finally, the competitive environment of cooperative banks and the interconnections among financial intermediaries can generate spillover effects, enhancing the technical efficiency of small banks (Algeri et al., 2022).

3.2.2 Organized crime and banking

While the determinants of banking efficiency have been extensively investigated, no study has specifically explored the impact of organized crime on the efficiency of cooperative banks. The literature has instead focused on how criminal networks affect credit markets and firms' access to finance.

Previous literature examined various external factors influencing banks' efficiency, but none has specifically addressed the impact of organized crime on this dimension. Criminal networks can exacerbate key aspects of CCBs' operations. For instance, banks tend to charge higher interest rates and demand more collateral from firms operating in areas plagued by criminal syndicates (Bonaccorsi di Patti, 2009; de la Miyar, 2016). Consistently, Mocetti and Rizzica (2024) confirm that organized crime increases borrowing costs and reduces credit availability for Italian firms, while Bianchi et al. (2022) attribute these effects to heightened risk perceptions that prompt banks to tighten lending standards toward businesses in areas dominated by criminal organizations. Judicial and anti–mafia law enforcement actions can partially mitigate these issues. Such interventions have been shown to reduce credit constraints and increase bank lending to businesses in the affected regions (Jappelli et al., 2005; Buchetti et al., 2025). However, they may also lead to higher borrowing costs, as banks often reassess risk upwards in the aftermath of mafia infiltration. This implies that, while dismantling criminal networks can improve credit access, the lingering influence of organized crime continues to shape banks' risk assessments. Overall, this stream of literature highlights the sensitivity of banking activity to the presence of organized crime. Given their closer ties to local economies, cooperative credit banks may be even more exposed than larger banks to the risks associated with criminal syndicates, making it crucial to investigate this relationship further.

This stream of research underscores the sensitivity of financial intermediation to the presence of organized crime, yet leaves open an important question: does organized crime also affect how efficiently banks operate?

A cooperative is founded on an intergenerational endowment without final owners, a structure that entails distinctive governance challenges. Among the risks are the use of resources for purposes misaligned with members' best interests–such as empire–building–and attempts at appropriation. The likelihood of empire–building can be amplified by mechanisms that encourage capital accumulation and create asymmetric opportunities for consolidation (Fonteyne, 2007). This governance framework also raises specific concerns in relation to organized crime. Criminal networks may interfere with the proper management of resources, whether by infiltrating boards and committees or by exerting pressure and threats on managers and directors. Such interference can divert cooperative resources toward illicit ends and undermine operational efficiency. The aim of this paper is therefore to assess whether the efficiency of CCBs is affected by the presence of organized crime in the province where the bank is headquartered. In particular, this work addresses the following research question:

- RQ: Does the presence of organized crime in a local area affect the efficiency of cooperative credit banks?

The main contribution of this analysis lies in extending the literature on banking efficiency by introducing a previously unexplored factor–organized crime. While prior studies have shown that criminal infiltration can distort credit markets and increase borrowing costs for firms, no empirical research has yet examined its implications for banks' operational efficiency. CCBs are considered here because of their intrinsically local orientation: while this provides advantages in terms of local knowledge and community engagement, it may also render them more vulnerable to the influence of organized crime in local markets.

3.3 Data and methodology

The empirical analysis relies on a panel of 235 Italian cooperative banks observed over the period 2011–2019. Data are sourced from Orbis Bank Focus and refer to unconsolidated accounts, including both standalone statements and consolidated companion accounts. A regional breakdown of the sample is provided in Table 3.1.

In this paper, technical and cost efficiency are estimated through Stochastic Frontier Analysis (SFA), a parametric approach based on the premise that economic agents cannot surpass the optimal frontier, and that any deviation from it reflects individual inefficiencies (Belotti et al., 2013). The analysis investigates the impact of organized crime on both technical and cost efficiency by employing a "true" random effects model, which disentangles time–varying inefficiency from firm–specific, time–invariant heterogeneity (Greene, 2005). The model specification is presented as follows:

$$y_{it} = \alpha + \mathrm{x}'_{it}\beta + \nu_{it} - S\upsilon_{it} + \omega_i \tag{3.1}$$

TABLE 3.1: Sample distribution by region.

Region	CCBs	Region	CCBs
Abruzzo	7	Lombardy	26
Aosta Valley	1	Marche	14
Apulia	24	Molise	2
Basilicata	2	Piedmont	8
Calabria	5	Sardinia	2
Campania	13	Sicily	13
Emilia–Romagna	12	Trentino–South Tyrol	53
Friuli–Venezia Giulia	8	Tuscany	14
Lazio	17	Umbria	1
Liguria	-	Veneto	13

where α denotes the constant, x' is a vector of explanatory variables, and β represents the associated parameters. The composite error term consists of two components: a symmetric noise term (ν_{it}), assumed to be normally distributed with zero mean and homoskedastic variance, and an inefficiency term (v_{it}), defined as the deviation from the maximum attainable output given the inputs. The sign of the inefficiency component, S, depends on the type of frontier under consideration, being set to +1 for production functions and –1 for cost functions. The inefficiency term v_{it} is assumed to follow an exponential distribution (i.e., a normal–exponential specification). In addition, a time–invariant term (ω_i) captures firm–specific heterogeneity across banks. The normalized stochastic production function is specified in a trans–logarithmic form, as follows:

$$\begin{aligned}\ln Q_{it} = & \eta + \sum_{k=1}^{3} \xi_k lnP_{kit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \varrho_{kj} lnP_{kit} lnP_{jit} + \gamma t + \frac{1}{2}\sum_{k=1}^{3} \theta_k lnP_{kit} t \\ & + \frac{1}{2}\psi t^2 + (\nu_{it} - v_{it}) + \omega_i \end{aligned} \tag{3.2}$$

where Q_{it} denotes output, proxied by total assets. The model includes three input prices, P_1, P_2, and P_3. Specifically, P_1 refers to the price of labor, calculated as the ratio of staff expenses to total assets. P_2 represents the price of physical capital, computed as the ratio of other administrative and operating expenses to fixed assets. Finally, P_3 denotes the price of borrowed funds, measured as the ratio of total interest expenses to total liabilities. The normalized stochastic cost function is specified in a trans–logarithmic form, as follows:

$$\begin{aligned}\ln C_{it} =& \eta_0 + \eta_1 \ln Q_{it} + \frac{1}{2}\eta_2 \ln Q_{it}^2 + \sum_{k=1}^{3} \xi_k lnP_{kit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \rho_{kj} lnP_{kit} lnP_{jit} \\ &+ \frac{1}{2}\sum_{k=1}^{3} \varrho_k lnQ_{it} lnP_{kit} + \gamma t + \frac{1}{2}\phi lnQ_{it} t + \frac{1}{2}\sum_{k=1}^{3} \theta_k lnP_{kit} t + \frac{1}{2}\psi t^2 \\ &+ (\nu_{it} + \upsilon_{it}) + \omega_i\end{aligned} \tag{3.3}$$

where C_{it} denotes total cost, measured by total operating expenses, while the output and input variables are defined consistently with the production function (Algeri et al., 2022). To account for technological progress over time–such as that induced by the reform of Italian cooperative banks–a deterministic time trend is incorporated into both the production and cost functions. Specifically, the model includes a linear trend (t), its squared term (t^2) to capture potential non–linear dynamics, and interaction terms between the time trend and the input variables (as well as the output variable in the cost function).

To sum up, the presence of organized crime (OC) enters the model through the efficiency variance function (σ_{uit}). The variable is measured by means of a composite index developed by Forgione et al. (2024), which represents the provincial–level version of the organized crime index constructed at the municipal level by Forgione and Migliardo (2025). The index employed in this study is estimated using the Robust Multi–directional Benefit of the Doubt (RMdirBoD) approach proposed by Vidoli et al. (2024). This methodology refines the procedure introduced by Fusco (2023) by incorporating multidirectional optimization and robust estimation techniques, thereby addressing problems of compensability and the presence of outliers. The provincial–level composite indicator of organized crime was developed using official data from the Italian Ministry of the Interior on offenses typically associated with organized crime syndicates, along with publicly available information on the presence of mafia groups across provinces. The resulting composite indicator ranges from 0 to 1, with higher values denoting greater intensity and diffusion of organized crime at the provincial level. The estimation of both the production and cost frontiers, together with the coefficients of the efficiency determinants, is carried out simultaneously using the one–step

TABLE 3.2: Variables definition.

Variable	Definition
Total Assets	Bank's total assets, winsorized at 1% level.
Total Operating Expense	Bank's total operating expense, winsorized at 1% level.
Labor Cost	Staff expense/total assets, winsorized at 1% level.
Physical Capital Price	(Other administrative expense+other operating expense)/fixed assets, winsorized at 1% level.
Borrowed Funds Price	Total interest expense/total liabilities, winsorized at 1% level.
OC	Organized crime index (Forgione et al., 2024).
IQI	Institutional quality index (Forgione and Migliardo, 2025).
Size	Natural logarithm of the number of employees, winsorized at 1% level.
Macroregion	
Northwest	Cooperative bank headquartered in Northwest of Italy.
Norteast	Cooperative bank headquartered in Northeast of Italy.
Centre	Cooperative bank headquartered in Centre of Italy.
South and islands	Cooperative bank headquartered in South and islands of Italy.

procedure of Battese and Coelli (1995), which avoids the bias typically associated with the two–stage method (Schmidt, 2011). The inefficiency equation includes the *OC* variable as well as an institutional quality index (*IQI*) (Agostino et al., 2023). The rationale is that inefficiency may also reflect a more uncertain economic environment, such as weaker institutional quality in provinces with high criminal infiltration. In this work, the *IQI* is taken from Forgione and Migliardo (2025), who developed it at the jurisdictional level of the justice of the peace using the RMdirBoD methodology. This measure is preferred to the institutional quality index proposed by Nifo and Vecchione (2015), as the latter incorporates crime indicators, which may cause collinearity with the *OC* index. Finally, the set of control variables includes the size of cooperative credit banks (*Size*), defined as the natural logarithm of the number of employees, as well as four geographical dummies based on Italy's standard division into macro–regions (*Northwest*, *Northeast*, *Centre*, *South*).

$$u_{it} = f(OC_{it}, IQI_{it}, Size_{it}, \sum_{j=2}^{4} Macroregion_j) \tag{3.4}$$

In this analysis, the impact of *OC* and *IQI* is evaluated at the level of CCBs' headquarters, in line with the research hypotheses. The aim is to assess how governance mechanisms may be influenced by the presence of organized crime, with potential consequences for both technical and cost efficiency.

Table 3.2 provides the definitions of all variables employed in this study, while the summary statistics are reported in Table 3.3.

3.4 Empirical results

The empirical results reported in Table 3.4 illustrate the impact of the organized crime composite index on banks' technical inefficiency. The findings

TABLE 3.3: Summary statistics.

Variable	Minimum	Maximum	Mean	Standard deviation
Total Assets	56,179	11,100,000	1,040,056	1,563,998
Total Operating Expense	1,349	189,319	19,993.980	28,729.18
Labor Cost	0.316	1.997	1.111	0.290
Physical Capital Price	25.790	1,278.235	120.246	167.907
Borrowed Funds Price	0.151	1.985	0.816	0.472
OC	0.016	1	0.295	0.223
IQI	0.601	1	0.914	0.073
Size	2.197	7.153	4.405	1.058
Northwest	0	1	0.149	0.356
Northeast	0	1	0.366	0.482
Centre	0	1	0.196	0.397
South	0	1	0.289	0.454

Accounting data are expressed in thousand Euros.

reveal a positive and statistically significant effect at the 5% level. In other words, CCBs headquartered in areas with a stronger presence of criminal syndicates experience higher levels of technical inefficiency, thereby confirming the research hypothesis advanced in this study. A plausible explanation for this outcome lies in the potential infiltration of organized crime into the governance structures of cooperative banks. Criminal presence may compromise decision–making processes in multiple ways. First, individuals linked to organized crime within governing bodies may influence investment or credit allocation decisions according to particularistic interests rather than economic or prudential considerations. Such behavior inevitably generates operational inefficiencies, stemming from misallocation of resources and the accumulation of poorly managed financial risks. Second, criminal infiltration may undermine internal control systems. The presence of criminal actors reduces the ability of supervisory bodies to promptly address opportunistic or inefficient practices, thereby producing systemic inefficiencies and raising operational costs related to compliance and reputational risks. By contrast, the institutional quality index (*IQI*) is associated with lower levels of technical inefficiency, in line with the evidence reported by Agostino et al. (2023). Finally, with respect to geographical heterogeneity, CCBs headquartered in Southern Italy and the islands exhibit significantly higher levels of technical efficiency, consistent with previous findings (Battaglia et al., 2010).

Moreover, the estimated production frontier highlights a significant and positive time trend in total assets, coupled with a negative interaction effect with labor. These results suggest that, although the productive capacity of cooperative banks has generally increased over time, the marginal contribution of labor to this expansion has diminished. The time–trend coefficient remains statistically significant and robust across alternative specifications, pointing to a persistent temporal dynamic in efficiency performance. This evidence supports the view that bank operations are evolving–likely driven by technological progress, learning effects, or institutional adjustments–and that such temporal dynamics must be taken into account when assessing the efficiency–cost implications of organized crime.

The analysis of the cost function, reported in Table 3.5, also reveals a positive and statistically significant coefficient for the impact of *OC* on banks' cost inefficiency. Consistent with the results on technical efficiency, cooperative banks headquartered in provinces with a strong presence of organized crime exhibit lower cost efficiency, suggesting that they incur additional or distorted costs to produce the same level of output. Several mechanisms may account for this reduction in cost efficiency. First, banks may be compelled–either explicitly or implicitly–to engage with suppliers or service providers linked to criminal networks, often under inflated prices or non–competitive contractual conditions. Second, governance distortions caused by criminal infiltration can lead to inefficient resource allocation, including overstaffing, the selection of suboptimal input mixes, or the misuse of capital in ways inconsistent with cost minimization. Third, operating in a high–crime environment may increase expenditures related to security, compliance, legal services, and risk premiums, all of which further erode cost efficiency. Interestingly, and unlike the results for technical efficiency, institutional quality does not exhibit a significant effect on cost efficiency in the estimates, diverging from the findings of Agostino et al. (2023). A possible explanation lies in the unit of analysis: in this work, estimates are conducted at the level of bank headquarters. While institutional quality may exert a stronger influence at the branch level–where daily transactions, customer relations, and direct exposure to local enforcement are more salient–it may play a comparatively limited role in shaping cost structures at the headquarters level. This distinction could explain the lack of statistical significance observed in this dimension.

When examining the temporal dimension, the cost frontier confirms the presence of significant time dynamics, albeit with some nuances. In both model specifications, the coefficients of the linear time trend and its squared

TABLE 3.4: One–step stochastic frontier estimates for production function.

	(1)	(2)
$\ln P_1$	-0.431***(0.028)	-0.529***(0.030)
$\ln P_2$	-0.014**(0.006)	-0.010(0.011)
$\ln P_3$	0.055***(0.010)	0.080***(0.017)
$1/2 \times \ln P_1 \times \ln P_2$	-0.056(0.034)	-0.400***(0.063)
$1/2 \times \ln P_1 \times \ln P_3$	-0.135***(0.045)	0.089(0.139)
$1/2 \times \ln P_2 \times \ln P_3$	0.041*(0.022)	0.045(0.059)
t	0.039***(0.003)	0.045***(0.006)
$1/2 \times t \times \ln P_1$	-0.075***(0.021)	-0.015(0.040)
$1/2 \times t \times \ln P_2$	-0.007(0.006)	-0.009(0.020)
$1/2 \times t \times \ln P_3$	-0.005(0.014)	0.033(0.026)
$1/2 \times t^2$	0.003(0.002)	0.007*(0.004)
$1/2 \times (\ln P_1)^2$	0.009(0.065)	-0.021(0.063)
$1/2 \times (\ln P_2)^2$	-0.007(0.012)	0.010(0.024)
$1/2 \times (\ln P_3)^2$	-0.019(0.030)	0.039(0.053)
Intercept	13.386***(0.012)	13.188***(0.011)
σ_v		
OC		1.805**(0.786)
IQI		-4.726**(2.174)
Size		0.020(0.156)
Northwest		*Benchmark*
Northeast		0.449(0.385)
Centre		0.004(0.437)
South and islands		-1.361**(0.556)
Intercept		-0.060(2.150)
$E(\sigma_v)$		0.138
σ_v		0.027***(0.008)
Number of observations	1,686	1,638

Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

term are positive and statistically significant, particularly in the more comprehensive specification. This suggests that total operating expenses have increased over time at an accelerating rate. Among the interaction terms with time, only the interaction between time and borrowed funds is consistently positive and statistically significant. This finding indicates that, over time, the cost burden associated with borrowed funds has grown disproportionately, possibly reflecting tighter financial conditions or structural changes in banks' funding sources. By contrast, the other time–input interactions are not statistically significant, pointing to relative temporal stability in the marginal cost of labor and physical capital. Overall, these results highlight the importance of accounting for dynamic factors when analyzing efficiency patterns, particularly in relation to cost behavior.

To further assess the economic impact of organized crime on CCBs' efficiency, the economic magnitude of the main findings has been computed. Specifically, a one–standard–deviation increase in organized crime presence is associated with losses of 22.9 and 33.7 percentage points in technical and cost efficiency, respectively. In the same vein, comparing banks operating in high–crime areas (above the 75th percentile) with those located in areas with a lower presence of criminal syndicates (below the 25th percentile) leads to efficiency losses of 20.5 and 0.3 percentage points, respectively. From an economic perspective, these efficiency losses imply that cooperative banks in high–crime areas face greater operational frictions and are less able to convert inputs into productive outputs. Lower cost efficiency means that a larger share of labor, security, and administrative resources must be allocated to activities such as compliance, monitoring, and protection rather than to credit intermediation. The large gap in technical efficiency suggests a reduced capacity to expand lending or asset volumes for a given input mix. Overall, organized crime diverts resources away from productive uses and forces banks to operate below their potential scale.

To further validate the comparison between high– and low–crime areas, both the production and cost functions are re–estimated to account for the possibility that organized crime exerts an effect only above the 75th percentile, following the procedure proposed by Hansen (2000). In particular, within the inefficiency determinants, the crime indicator has been split at the 75th percentile to allow the marginal effect of crime to differ across the two regimes. The empirical results are reported in Table 3.6 and Table 3.7.

TABLE 3.5: One–step stochastic frontier estimates for cost function.

	(1)	(2)
$\ln Q$	0.988***(0.025)	0.957***(0.010)
$\ln P_1$	0.843***(0.034)	0.859***(0.025)
$\ln P_2$	0.049(0.032)	0.014(0.012)
$\ln P_3$	-0.017(0.017)	-0.008(0.011)
$1/2 \times \ln Q \times \ln P_1$	0.012(0.040)	0.032(0.047)
$1/2 \times \ln Q \times \ln P_2$	-0.028(0.043)	-0.039**(0.018)
$1/2 \times \ln Q \times \ln P_3$	-0.031**(0.014)	-0.026*(0.014)
$1/2 \times \ln P_1 \times \ln P_2$	0.113**(0.045)	0.148***(0.043)
$1/2 \times \ln P_1 \times \ln P_3$	0.088(0.097)	0.017(0.062)
$1/2 \times \ln P_2 \times \ln P_3$	-0.078(0.059)	-0.047(0.030)
t	0.005(0.005)	0.010***(0.003)
$1/2 \times t \times \ln Q$	-0.008(0.005)	-0.002(0.004)
$1/2 \times t \times \ln P_1$	0.016(0.023)	-0.006(0.016)
$1/2 \times t \times \ln P_2$	0.004(0.014)	0.011(0.009)
$1/2 \times t \times \ln P_3$	0.026**(0.012)	0.027**(0.013)
$1/2 \times t^2$	0.004***(0.001)	0.003**(0.001)
$1/2 \times (\ln Q)^2$	0.067*(0.039)	0.003(0.010)
$1/2 \times (\ln P_1)^2$	-0.293**(0.125)	-0.291***(0.090)
$1/2 \times (\ln P_2)^2$	-0.120***(0.021)	-0.108***(0.015)
$1/2 \times (\ln P_3)^2$	0.009(0.028)	0.021(0.025)
Intercept	9.933***(0.013)	9.969***(0.010)
σ_v		
OC		1.901**(0.735)
IQI		-2.531(2.194)
Size		0.502(0.360)
Northwest		*Benchmark*
Northeast		-0.281(0.450)
Centre		1.297(0.878)
South and islands		0.360(0.710)
Intercept		-6.910***(2.646)
$E(\sigma_v)$		0.051
σ_v		0.030***(0.004)
Number of observations	1,686	1,638

Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

TABLE 3.6: One–step stochastic frontier estimate for production function with threshold.

$\ln P_1$	-0.491***(0.019)
$\ln P_2$	-0.062***(0.009)
$\ln P_3$	0.048***(0.016)
$1/2 \times \ln P_1 \times \ln P_2$	-0.134***(0.027)
$1/2 \times \ln P_1 \times \ln P_3$	-0.012(0.069)
$1/2 \times \ln P_2 \times \ln P_3$	0.036(0.030)
t	0.038***(0.004)
$1/2 \times t \times \ln P_1$	-0.067***(0.018)
$1/2 \times t \times \ln P_2$	-0.012*(0.007)
$1/2 \times t \times \ln P_3$	0.030**(0.015)
$1/2 \times t^2$	0.005**(0.002)
$1/2 \times (\ln P_1)^2$	-0.312***(0.062)
$1/2 \times (\ln P_2)^2$	0.019**(0.009)
$1/2 \times (\ln P_3)^2$	0.047(0.033)
Intercept	13.277***(0.016)
σ_v	
OC	-1.049(0.953)
$OC > 75^{th}$ *percentile*	2.430***(0.857)
IQI	-5.511***(1.984)
Size	-0.012(0.138)
Northwest	*Benchmark*
Northeast	0.275(0.364)
Centre	0.005(0.413)
South and islands	-1.518***(0.488)
Intercept	1.425(1.864)
$E(\sigma_v)$	0.142
σ_v	0.021***(0.006)

Number of observations: 1,638. Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

TABLE 3.7: One–step stochastic frontier estimate for cost function with threshold.

$\ln Q$	0.957***(0.010)
$\ln P_1$	0.859***(0.025)
$\ln P_2$	0.014(0.012)
$\ln P_3$	-0.008(0.011)
$1/2 \times \ln Q \times \ln P_1$	0.033(0.047)
$1/2 \times \ln Q \times \ln P_2$	-0.039**(0.018)
$1/2 \times \ln Q \times \ln P_3$	-0.026*(0.014)
$1/2 \times \ln P_1 \times \ln P_2$	0.148***(0.043)
$1/2 \times \ln P_1 \times \ln P_3$	0.017(0.063)
$1/2 \times \ln P_2 \times \ln P_3$	-0.047(0.029)
t	0.010***(0.003)
$1/2 \times t \times \ln Q$	-0.002(0.004)
$1/2 \times t \times \ln P_1$	-0.006(0.016)
$1/2 \times t \times \ln P_2$	0.011(0.009)
$1/2 \times t \times \ln P_3$	0.028**(0.013)
$1/2 \times t^2$	0.003**(0.001)
$1/2 \times (\ln Q)^2$	0.003(0.010)
$1/2 \times (\ln P_1)^2$	-0.290***(0.090)
$1/2 \times (\ln P_2)^2$	-0.108***(0.015)
$1/2 \times (\ln P_3)^2$	0.021(0.025)
Intercept	9.969***(0.010)
σ_v	
OC	1.494(1.318)
$OC > 75^{th}$ *percentile*	0.368(1.065)
IQI	-2.508(2.194)
Size	0.506(0.355)
Northwest	*Benchmark*
Northeast	-0.283(0.451)
Centre	1.326(0.849)
South and islands	0.337(0.722)
Intercept	-6.888**(2.674)
$E(\sigma_v)$	0.051
σ_v	0.030***(0.004)

Number of observations: 1,638. Robust standard errors are reported in parentheses. ***, ** and * represent respectively significance at 1%, 5% and 10%.

Analyzing the impact of organized crime above and below the 75^{th} percentile of the indicator, the interaction term is statistically significant for technical efficiency, whereas it is not significant for cost efficiency. This indicates that the effect of organized crime does not vary systematically across low— and high–crime environments with respect to cost–side efficiency, confirming the evidence from the economic magnitude. Consistent with this result, the very small difference in cost efficiency between high– and low–crime areas (0.3 percentage points) aligns with the absence of nonlinearities. Therefore, this relationship appears to be approximately linear, with no evidence of threshold–type nonlinear effects.

While both technical and cost efficiency are negatively affected by the presence of organized crime, the underlying mechanisms appear to differ. In the case of technical efficiency, the main channel is more directly linked to governance infiltration and institutional fragility. By contrast, for cost efficiency, distortions in input choices and price–setting mechanisms driven by criminal influence play a more prominent role. Overall, the results suggest that organized crime is systematically associated with lower efficiency in cooperative banks across both dimensions. Governance–related mechanisms–such as infiltration into decision–making structures–better explain the decline in technical efficiency, whereas operational and market distortions–such as inflated input prices or suboptimal input combinations–provide a stronger rationale for the deterioration in cost efficiency. Finally, institutional quality emerges as a mitigating factor for technical efficiency but not for cost efficiency, a divergence likely attributable to the headquarters–level perspective of the analysis, where local institutional dynamics exert a weaker influence.

3.5 Concluding remarks

The analysis of bank efficiency represents a crucial issue for practitioners, policymakers, and the broader economic system. Cooperative banks, in particular, play a pivotal role due to their local orientation, which fosters credit availability, financing, and regional economic growth. Against this backdrop, it becomes essential to assess not only the internal drivers of efficiency but also the contextual conditions in which CCBs operate. The main objective of this study was to investigate whether one such contextual factor–namely, the presence of organized crime–affects both technical and cost efficiency.

A wide range of studies has investigated the influence of external factors on the efficiency of cooperative banks. For example, Battaglia et al. (2010) examined the role of local economic conditions, while Agostino et al. (2023) analyzed the effect of institutional quality. However, no previous research has explored in depth how criminal networks may affect the activities of CCBs by distorting decision–making processes, weakening governance mechanisms, and undermining control systems.

To address this gap, the present analysis applied Stochastic Frontier Analysis to investigate whether the presence of criminal syndicates leads to losses in banks' efficiency. The estimation relied on trans–logarithmic functions and explicitly accounted for technological progress. The presence of organized crime was measured through the composite indicator developed by Forgione et al. (2024). The empirical results show that banks operating in areas characterized by a strong presence of organized crime experience a statistically significant reduction in efficiency scores. In addition, institutional quality was controlled for using the *IQI* proposed by Forgione and Migliardo (2025). Findings indicate that stronger institutions are associated with improvements in technical efficiency, but not in cost efficiency. This result may be explained by the fact that the analysis was conducted at the headquarters level.

The findings suggest that although both technical and cost efficiency are adversely affected by the presence of organized crime, the underlying mechanisms differ. Technical efficiency appears to be primarily undermined by governance infiltration and institutional fragility, whereas cost efficiency is more strongly influenced by distortions in input choices and price–setting mechanisms associated with criminal influence. Overall, the evidence indicates that organized crime is systematically linked to lower efficiency in cooperative banks across both dimensions. Governance–related mechanisms–such as infiltration into decision–making structures–are more relevant for explaining the decline in technical efficiency, while operational and market distortions–such as inflated input costs or suboptimal input combinations–better account for the deterioration in cost efficiency. Moreover, institutional quality emerges as a mitigating factor for technical efficiency, but not for cost efficiency. This divergence is likely explained by the focus on headquarters–level data, where local institutional dynamics exert a weaker influence.

Despite the key findings of this study, some limitations should be acknowledged. First, the development of an alternative institutional quality index at the provincial level–one that does not incorporate crime–related variables–would be desirable in order to provide more nuanced insights into this crucial relationship. Second, the analysis was conducted at the headquarters level of cooperative banks only. Future research could extend the scope to include bank branches and different types of financial institutions, thereby allowing a broader assessment of the impact of organized crime on banking activity and of the moderating role played by institutional quality. In this sense, it could be possible not only to enrich academic research but also to provide policymakers and regulatory authorities with more effective tools to strengthen governance mechanisms and reduce the adverse impact of criminal networks on the financial system.

Chapter 4

Between Fear and Finance: How Organized Crime Perceptions Influence Credit Rationing[6]

Abstract

This study examines the influence of the presence of perceived organized crime on firms' access to financial resources. The analysis is based on an original survey conducted by the Bank of Italy, involving a representative sample of Italian firms belonging to all sectors, regarding the perceived organized crime risk and the condition of being credit rationed by banks. The findings show that areas and sectors at higher risk of extortion, threats, and intimidation are characterized by credit rationing policies. Moreover, extortion has emerged as the most negative factor significantly increasing the likelihood of credit rationing. The empirical evidence highlights the distorsive effect of organized crime on the credit market by increasing financing costs, exacerbating adverse selection, and causing banks to adopt risk–averse lending practices. On the other hand, more efficient firms exhibit lower probability of being credit rationed. The findings suggest that policymakers and financial institutions should consider the adverse effect of organized crime in risk assessment models and implement targeted financial support measures to mitigate the negative effects of criminal networks on credit markets.

[6]Parts of this chapter have been published in the *International Review of Economics & Finance* as: [Antonio Fabio Forgione, Carlo Migliardo, Marco Spadaro] (2025), "Crime and credit: Analyzing the impact of organized crime perceptions on loan restrictions", in the [International Review of Economics & Finance], Volume 104, 104669, DOI: https://doi.org/10.1016/j.iref.2025.104669.

4.1 Introduction

The presence of criminal organizations poses a persistent challenge to institutions and society, and Italy serves as an appropriate case study, as in certain regions of its territory, the perceived existence of organized crime is substantial and significantly impacts economic activities, impeding their growth. Indeed, illicit activities conducted by mafia groups exert a considerable influence on the heterogeneity of economic development, public safety, and social progress in specific areas of Italy. 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 boosts 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 negative impact of organized crime on the academic performance of elementary school students is substantial. Mafia's influence disrupts the incentive structure, which deters students and their families from committing resources to education. Equally, it discourages local firms from employing individuals with higher education levels (Cavalieri et al., 2023).

An adverse environment as a result of mafias presence deteriorate also the local financial system. Specifically, credit allocation is not immune to the adverse impact of a negative environment. 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, small and medium–sized firms 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.

The increase in credit costs in high–crime areas can also be directly attributed to the increased risk perceived by financial institutions. Banks operating in environments where extortion, intimidation, or criminal infiltration are common often compensate for this risk by imposing higher interest rates or stricter collateral requirements. As shown by Bottoni et al. (2024), this increase in financing costs exacerbates the problem of adverse selection, where the riskiest firms or those potentially colluding with criminal organizations are disproportionately represented. Consequently, banks face a pool of applicants with higher average risk, thereby perpetuating the vicious cycle of adverse selection. Similarly, a rise in the cost of credit can encourage opportunistic and risky behavior by firms, creating a moral hazard problem. Firms operating under the influence of organized crime may adopt riskier strategies, relying on the protection or support of criminal organizations to mitigate potential losses. This not only increases the risk of default for banks, but also contributes to an overall distortion in lending dynamics, leading to a further tightening of credit access conditions. Balletta and Lavezzi (2023) demonstrated that the extortion imposed by organized crime syndicates on legal firms exhibits a strong concave relationship with firm size and is highly regressive. Specifically, small firms were extorted up to 40% of their profits, while large firms were extorted only 2%. This, along with the establishment of obstacles to entry and implying unsustainable costs, leads to decreased profitability and constraints on smaller firms' capacity to accumulate sufficient collateral for obtaining additional credit.

Furthermore, it has been documented that court efficiency directly impacts the availability of loans (Jappelli et al., 2005). In this vein, it should be observed that in regions with significant organized crime, judicial efficiency suffers, impacting criminal justice and civil courts. Rodano (2021) notes that judicial districts with high organized crime rates experience prolonged bankruptcy proceedings. These delays undermine timely resolutions and have economic repercussions, such as higher credit costs for businesses due to the extended uncertainty for creditors recovering assets. This suggests that focusing resources on criminal repression in high–crime areas diminishes civil court efficiency, leading to increased workloads.

Credit allocation is not immune to the adverse impacts of a negative environment, 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 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 no 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 literature by examining whether the perception of organized crime influence could increase the likelihood of credit rationing. While the broader economic costs of organized crime have been extensively documented, a significant gap remains regarding how the perception of organized crime influences credit allocation decisions at the firm level. Specifically, no prior study has directly examined the impact of crime–related risk perceptions on credit rationing. This study aims to fill this gap by leveraging a unique dataset from the Bank of Italy, which captures firms' perceptions of organized crime risks and their experiences with credit rationing. By analyzing data from a representative survey of industrial and service companies, a more nuanced understanding of how organized crime spread influences financial accessibility is provided.

Addressing this gap is crucial for both policymakers and financial institutions because efforts to improve credit accessibility in affected regions may fall short without a clear understanding of these dynamics

Section 4.2 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 4.3. Section 4.4 provides the empirical results and Section 4.5 concludes the study.

4.2 Background literature

This section reviews the two main strands of literature underlying this study: the mechanisms and determinants of credit rationing, and the economic distortions induced by organized crime. The purpose is to identify how criminal presence and its perception may influence firms' access to finance.

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.

4.2.1 Credit rationing

Credit rationing occurs when loan seekers with comparable characteristics are selectively approved or denied, regardless of their willingness to accept higher interest rates. This scenario may also occur when specific borrowers are unable to secure loans at any interest rate, despite the fact that they would be eligible if there were more credit options available. Concurrently, firms' access to credit is substantially impeded by ex post frictions, including moral hazard, costly monitoring, and limited contract enforceability.

The theoretical literature has effectively elucidated credit market inefficiencies and financial constraints caused by asymmetric information between borrowers and lenders. When only the former party possesses information regarding its creditworthiness, which lenders cannot access, the resulting market equilibrium is marked by adverse selection and credit rationing (Keeton, 1979; Stiglitz and Weiss, 1981). Credit rationing is also caused by ex post information asymmetries, specifically due to moral hazard implications (Boot and Thakor, 1994).

Collateral plays a crucial role for banks in mitigating informational asymmetries and addressing credit rationing. Banks use collateral when interest rates are ineffective due to indirect impacts on credit portfolio quality. By pairing collateral with an optimal interest rate, an equilibrium that resolves credit rationing can be reached. Numerous theories discuss the role of collateral in reducing informational asymmetries[7].

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

[7] For a comprehensive theoretical review, see Coco (2000), for empirical insights Steijvers and Voordeckers (2009).

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.

While the above literature has extensively documented how informational frictions, firm characteristics, and relationship lending shape credit rationing, little attention has been paid to how contextual factors–such as the local socio–institutional environment and the presence of criminal organizations–may alter credit allocation mechanisms. The next subsection explores how organized crime can distort markets and potentially affect credit supply decisions.

4.2.2 The role of organized crime in shaping market distortions

The impact of 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 reasons which lie 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 the presence of criminal network pressure reduces firms' technical efficiency and their tendency to invest (Forgione and Migliardo, 2023b; Forgione and Migliardo, 2025). 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) have shown 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.

Despite extensive evidence on the economic costs of organized crime, little is known about whether and how the perception of criminal activity influences firms' access to finance. Drawing on insights from the literature on credit rationing and on market distortions induced by organized crime, this study addresses the following research question:

- RQ: Does the perception of organized crime influence firms' probability of experiencing credit rationing?

More specifically, it investigates whether the fear of organized crime–as perceived by entrepreneurs–acts as an informal constraint on credit markets, thereby increasing the likelihood of being credit rationed.

4.3 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]). 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*$_1$[8]; 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 the year 2020, are specified as follows:

$$\begin{aligned} Pr(Rationing_i = 1) = F(&\beta_0 + \beta_1 Organized\,Crime\,Risk_{ij} + \beta_2 Size_i \\ &+ \beta_3 Age_i + \beta_4 Geo\ Area_i + \beta_5 Performance_i \\ &+ \beta_6 Macro\ Sector_i + \beta_7 Export_i) \end{aligned} \tag{4.1}$$

$$\begin{aligned} Pr(Ordered\ Rationing_i = w) = Pr(&k_{w-1} < \beta_0 + \beta_1 Organized\,Crime\,Risk_{ij} \\ &+ \beta_2 Size_i + \beta_3 Age_i + \beta_4 Geo\ Area_i \\ &+ \beta_5 Performance_i + \beta_6 Macro\ Sector_i \\ &+ \beta_7 Export_i + u_i < k_w) \end{aligned} \tag{4.2}$$

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. Thus, it has been included 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[9], *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. To measure a firm's *Performance*, two alternative variables have been considered in the study (i.e. the multinomial variable *Operating Result*[10], and *Technical Efficiency*, estimated through Stochastic Frontier Analysis, as described in the Appendix C). Finally, the

[8]Barone and Masciandaro (2019) contend that criminal groups engage in usurious money lending not only to generate profit from interest rates but also as a mechanism for laundering illicit funds, either through direct or indirect means.

[9]0=20–49; 1=50–99; 2=100–199; 3=200–499; 4=500–999; 5=1000 workers or more.

[10]1=Large Profit; 2=Small Profit; 3=Broad Balance; 4=Small Loss; 5=Large Loss.

TABLE 4.1: 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?
Class 1		Not at all likely.
Class 2		Unlikely.
Class 3		Somewhat likely.
Class 4		Very likely.
Size	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	Multinomial variable	Five categories.
Technical Efficiency	Continuos variable	Technical efficiency estimated by rely on SFA.
Macro Sector	Multinomial variable	
Category 1		Manufacturing.
Category 2		Energy extraction.
Category 3		Non–financial private services.
Export	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.

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020].

models incorporate *Macro Sector*, that is a categorical variable which indicates the industry the enterprise is involved in, and the export share *Export*, 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 4.1 provides definitions of all the variables used in this study while summary statistics are reported in Table 4.2.

The sample comprises a diverse array of Italian firms from both industrial and service sectors across the country. The dependent variables employed in the investigation reveal considerable variability in access to bank loans. While the proportion of firms experiencing complete credit rationing is relatively low, the data suggest that a significant number of firms face challenges in securing necessary funding. The mean values of the variables, ranging from 1.355 to 1.502, indicate that while firms do not perceive these organized crime risks presence as particularly severe, a significant proportion of the sample considers them at least *quite likely*. The standard deviations reflect considerable variability in risk perception among firms, indicating heterogeneous levels of concern based on their respective operational contexts. Descriptive statistics indicate substantial variability in firm size, age, and technical efficiency, underscoring significant heterogeneity.

Table 4.3 presents the translog model estimates.

TABLE 4.2: Summary statistics.

Variable	Num. obs.	Mean	Std. dev.	Min	Max
Rationing	1,345	0.019	0.138	0	1
Ordered Rationing	1,328	0.139	0.398	0	2
$Organized\ Crime\ Risk_1$	1,345	1.484	0.760	1	4
$Organized\ Crime\ Risk_2$	1,343	1.502	0.765	1	4
$Organized\ Crime\ Risk_3$	1,340	1.355	0.640	1	4
Size	1,345	1.544	1.424	0	5
Geo Area	1,345	2.667	1.135	1	4
Age	1,345	39.500	24.260	...	...
Operating Result	1,345	2.613	1.262	1	5
Technical Efficiency	1,090	83.771	7.942	...	...
Macro Sector	1,345	1.586	0.894	1	3
Export	1,345	1.246	1.070	0	3

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

TABLE 4.3: Trans–log production function.

Variables	Coefficient
$\ln R_i$	0.687***(0.009)
$\ln L_i$	0.248***(0.011)
$\ln K_i$	0.052***(0.006)
$1/2(\ln R_i \times \ln L_i)$	-0.348***(0.012)
$1/2(\ln R_i \times \ln K_i)$	-0.024***(0.004)
$1/2(\ln L_i \times \ln K_i)$	0.029***(0.007)
$1/2(\ln R_i)^2$	0.180***(0.004)
$1/2(\ln L_i)^2$	0.158***(0.011)
$1/2(\ln K_i)^2$	0.006***(0.002)
Intercept	11.960***(0.013)

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Number of observations: 2,486. Standard errors are reported in parentheses, ***, ** and * represent respectively significance at 1%, 5% and 10%.

All coefficients showed statistical significance, substantiating the trans–log function's superior suitability for capturing heterogeneity within the sample. Indeed, given that the analysis encompasses firms operating across diverse sectors with varying production methods, factor utilization, technologies, and operational characteristics, the trans–log model provides a more accurate representation of these complexities than the Cobb–Douglas production function. The trans–log's flexibility in representing varying elasticities of substitution and capturing nonlinear effects further underscores its superiority, particularly in modeling interactions between production factors, which is crucial in a heterogeneous sample such as this.

4.4 Empirical results

The empirical findings reported in Table 4.4, in which *Rationing* and *Technical Efficiency* are considered and in Table 4.5, in which it has been investigated the effects of *Operating Result*, demonstrate that only the *Organized Crime Risk*$_3$ is statistically significant. The odds ratio indicates that the perception of the presence of threats, intimidation, or extortion increases the probability of experiencing credit rationing by more than 122% and 89%, respectively. The control variables are statistically insignificant except for the macro sector, referred to as energy extraction and *Performance*, but only when firm profitability is considered as a proxy.

Table 4.6, which considers *Ordered Rationing* and *Technical Efficiency*, and Table 4.7, which uses *Operating Result* to evaluate a firm's performance, show that all three risks associated with organized crime are statistically significant. The difference in results between the logit and ordered logit models concerning the significance of all types of organized crime presence associated with credit rationing can be explained by the inherently severe nature of extortion compared to other criminal threats considered in the INVIND sample. Extortion entails unexpected, coercive demands that can rapidly undermine the firm's financial management, since payments made under intimidation create unplanned financial strains, diminishing liquidity and jeopardizing solvency. This scenario indicates to banks that extorted firms are high–risk entities for default and consequently that extortion is the most significant criminal risk factor in logit models with binary credit rationing. The direct and immediate impact of extortion on firms may explain why usury and firms expropriation risk are less relevant in this model, but more relevant in the ordered logit model, which considers a broader range of credit

TABLE 4.4: Logit model with *Rationing* as dependent variable and *Technical Efficiency*.

Dependent variable	(1) *Rationing*	(2) *Rationing*	(3) *Rationing*
Independent variables			
Organized Crime Risk$_1$	0.386(0.263)		
Organized Crime Risk$_2$		0.273(0.257)	
Organized Crime Risk$_3$			0.801***(0.239)
Size	-0.163(0.200)	-0.181(0.195)	-0.155(0.185)
Northwest		*Benchmark*	
Northeast	-0.233(0.659)	-0.217(0.655)	-0.077(0.731)
Centre	-0.378(0.669)	-0.384(0.666)	-0.136(0.688)
South	-0.632(0.690)	-0.596(0.672)	-0.503(0.721)
Age	-0.012(0.014)	-0.012(0.013)	-0.011(0.013)
Technical Efficiency	0.010(0.025)	0.009(0.024)	0.011(0.026)
Manufacturing		*Benchmark*	
Energy Extraction	2.559***(0.905)	2.569***(0.919)	2.310**(0.938)
Non − financial Private Services	0.591(0.600)	0.607(0.600)	0.560(0.590)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.612(0.719)	-0.589(0.716)	-0.655(0.712)
Between 1/3 And 2/3 Of Turnover Exported	-0.532(0.986)	-0.489(0.978)	-0.532(0.973)
More Than 2/3 Of Turnover Exported	0.513(0.709)	0.505(0.717)	0.519(0.715)
Intercept	-4.602(2.944)	-4.374(2.850)	-5.567*(3.025)
	Odds ratio	Odds ratio	Odds ratio
Organized Crime Risk$_1$	1.471(0.878, 2.466)		
Organized Crime Risk$_2$		1.314(0.794, 2.173)	
Organized Crime Risk$_3$			2.227(1.395, 3.554)
Number of observations	1,090	1,090	1,087

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

TABLE 4.5: Logit model with *Rationing* as dependent variable and *Operating Result*.

Dependent variable	(1) *Rationing*	(2) *Rationing*	(3) *Rationing*
Independent variables			
Organized Crime Risk$_1$	0.218(0.259)		
Organized Crime Risk$_2$		0.159(0.256)	
Organized Crime Risk$_3$			0.641**(0.248)
Size	-0.111(0.182)	-0.124(0.173)	-0.097(0.171)
Northwest		*Benchmark*	
Northeast	-0.082(0.677)	-0.081(0.674)	0.055(0.750)
Centre	0.071(0.614)	0.071(0.615)	0.292(0.658)
South	-0.317(0.678)	-0.307(0.666)	-0.156(0.723)
Age	-0.012(0.012)	-0.011(0.012)	-0.010(0.012)
Large Profit		*Benchmark*	
Small Profit	1.780*(0.987)	1.774*(0.990)	1.575(0.967)
Broad Balance	1.527(1.098)	1.535(1.102)	1.450(1.061)
Small Loss	2.014*(1.069)	2.026*(1.071)	1.892*(1.053)
Large Loss	2.634**(1.017)	2.653***(1.015)	2.397**(1.004)
Manufacturing		*Benchmark*	
Energy Extraction	2.451***(0.825)	2.453***(0.833)	2.132**(0.894)
Non − financial Private Services	0.144(0.565)	0.146(0.565)	0.130(0.562)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-1.041(0.703)	-1.042(0.706)	-1.027(0.695)
Between 1/3 And 2/3 Of Turnover Exported	-0.691(0.811)	-0.674(0.810)	-0.674(0.818)
More Than 2/3 Of Turnover Exported	0.051(0.639)	0.042(0.642)	0.091(0.642)
Intercept	-5.312***(1.584)	-5.214***(1.590)	-5.989***(1.592)
	Odds ratio	Odds ratio	Odds ratio
Organized Crime Risk$_1$	1.244(0.749, 2.065)		
Organized Crime Risk$_2$		1.173(0.711, 1.935)	
Organized Crime Risk$_3$			1.897(1.168, 3.083)
Number of observations	1,345	1,343	1,340

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

TABLE 4.6: Ordered logit model with *Ordered Rationing* as dependent variable and *Technical Efficiency*.

Dependent variable	(1) *Ordered Rationing*	(2) *Ordered Rationing*	(3) *Ordered Rationing*
Independent variables			
Organized Crime Risk$_1$	0.263**(0.117)		
Organized Crime Risk$_2$		0.202*(0.118)	
Organized Crime Risk$_3$			0.311**(0.135)
Size	-0.109(0.074)	-0.118(0.074)	-0.116(0.074)
Northwest		*Benchmark*	
Northeast	-0.236(0.300)	-0.222(0.299)	-0.198(0.304)
Centre	-0.360(0.292)	-0.350(0.295)	-0.314(0.294)
South	-0.207(0.290)	-0.175(0.290)	-0.171(0.291)
Age	-0.009(0.006)	-0.009(0.006)	-0.008(0.006)
Technical Efficiency	-0.019**(0.009)	-0.019**(0.009)	-0.019**(0.009)
Manufacturing		Benchmark	
Energy Extraction	1.524***(0.492)	1.524***(0.496)	1.364***(0.499)
Non − financial Private Services	0.143(0.247)	0.144(0.248)	0.145(0.248)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.538*(0.279)	-0.546*(0.279)	-0.559**(0.281)
Between 1/3 And 2/3 Of Turnover Exported	-0.192(0.335)	-0.169(0.336)	-0.182(0.337)
More Than 2/3 Of Turnover Exported	0.123(0.310)	0.103(0.311)	0.110(0.311)
*Cut*1	0.084(0.918)	-0.030(0.913)	0.146(0.924)
*Cut*2	2.007(0.916)	1.890(0.912)	2.104(0.914)
	Odds ratio	Odds ratio	Odds ratio
Organized Crime Risk$_1$	1.301(1.034, 1.636)		
Organized Crime Risk$_2$		1.224(0.970, 1.543)	
Organized Crime Risk$_3$			1.364(1.048, 1.776)
Number of observations	1,078	1,078	1,076

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

rationing outcomes.

The estimates indicate that efficient firms are less prone to credit rationing, while firms exhibiting negative profitability (minor and substantial losses) are more susceptible compared to those in the model's benchmark (large profits). These findings are consistent across all three categories of organized crime threats to firms. Being older on the intensity of being credit rationed is negative. 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.

To test the robustness of the results to alternative measures of firm efficiency, the models are re–estimated by replacing the parametric efficiency

TABLE 4.7: Ordered logit model with *Ordered Rationing* as dependent variable and *Operating Result*.

Dependent variable	(1) *Ordered Rationing*	(2) *Ordered Rationing*	(3) *Ordered Rationing*
Independent variables			
$Organized\ Crime\ Risk_1$	0.156(0.108)		
$Organized\ Crime\ Risk_2$		0.145(0.111)	
$Organized\ Crime\ Risk_3$			0.246*(0.128)
Size	-0.109(0.068)	-0.113*(0.068)	-0.108(0.068)
Northwest		*Benchmark*	
Northeast	-0.031(0.276)	-0.026(0.275)	0.000(0.279)
Centre	-0.254(0.272)	-0.242(0.273)	-0.204(0.274)
South	-0.053(0.272)	-0.056(0.270)	-0.043(0.271)
Age	-0.009*(0.005)	-0.010*(0.005)	-0.010*(0.005)
Large Profit		*Benchmark*	
Small Profit	0.356(0.317)	0.349(0.318)	0.326(0.311)
Broad Balance	0.608*(0.367)	0.568(0.371)	0.559(0.367)
Small Loss	1.067***(0.348)	1.066***(0.348)	1.056***(0.343)
Large Loss	1.367***(0.346)	1.369***(0.347)	1.348***(0.343)
Manufacturing		*Benchmark*	
Energy Xxtraction	1.358***(0.516)	1.391***(0.517)	1.224**(0.522)
Non − financial PrivateServices	0.077(0.223)	0.105(0.224)	0.097(0.224)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.534**(0.252)	-0.525**(0.253)	-0.521**(0.255)
Between 1/3 And 2/3 Of Turnover Exported	-0.265(0.302)	-0.230(0.306)	-0.230(0.305)
More Than 2/3 Of Turnover Exported	-0.037(0.288)	-0.020(0.289)	-0.020(0.291)
*Cut*1	2.128(0.544)	2.114(0.547)	2.251(0.540)
*Cut*2	4.088(0.560)	4.067(0.564)	4.236(0.550)
	Odds ratio	Odds ratio	Odds ratio
$Organized\ Crime\ Risk_1$	1.169(0.945, 1.444)		
$Organized\ Crime\ Risk_2$		1.156(0.931, 1.437)	
$Organized\ Crime\ Risk_3$			1.279(0.995, 1.644)
Number of observations	1,328	1,327	1,324

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

indicator with a non–parametric score derived from Data Envelopment Analysis (DEA), a mathematical programming model that does not rely on assumptions about the production function (Charnes et al., 1978). Following Banker et al. (1984), an input–oriented DEA model with non–increasing returns to scale is computed using the same inputs and output adopted in the SFA estimation. This specification is appropriate in this context, as it accommodates potential scale inefficiencies while ruling out increasing returns to scale, which are uncommon among the medium and large manufacturing and service firms included in the INVIND sample.

Table 4.8 and Table 4.9 report the results for the logit and ordered logit models, respectively. The estimated coefficients confirm the robustness of the main findings: perceived organized crime risks remain positive and statistically significant, whereas the DEA efficiency score is negatively associated with credit rationing, indicating that more efficient firms face a lower probability of being credit constrained.

To address possible causality concerns and the possible mediation channel linking organized crime perceptions, firm efficiency, and credit access, a one–step SFA estimation has been conducted and it is reported in the Appendix C. Specifically, this specification allows testing whether perceptions of organized crime are associated with firms' technical inefficiency, providing indirect evidence on the mechanism through which crime perceptions may affect credit rationing.

Empirical results corroborate previous findings provided by Bonaccorsi di Patti (2009) and de la Miyar (2016). The empirical evidence aligns with and can be clarified by several and interconnected factors identified in the literature. Credit rationing exhibits a strong correlation with perceptions of organized crime, especially threats, intimidation, and extortion. This observation aligns with Arcuri and Levratto (2020) and Bianchi et al. (2022), who highlight how criminal activities erode trust, a fundamental element of financial agreements. In turn, this compels banks to adopt more restrictive lending practices to mitigate potential defaults in high–crime areas.

The findings further confirm that extortion, by creating unplanned financial burdens, exacerbates liquidity issues and jeopardizes firms' solvency, marking them as high–risk for financial institutions. Furthermore, evidence demonstrating the substantial influence of extortion on credit rationing align

TABLE 4.8: Logit model with *Rationing* as dependent variable and *DEA Efficiency*.

Dependent variable	(1) *Rationing*	(2) *Rationing*	(3) *Rationing*
Independent variables			
Organized Crime Risk$_1$	0.386(0.262)		
Organized Crime Risk$_2$		0.272(0.256)	
Organized Crime Risk$_3$			0.812***(0.233)
Size	-0.173(0.222)	-0.195(0.216)	-0.163(0.206)
Northwest		*Benchmark*	
Northeast	-0.242(0.661)	-0.229(0.658)	-0.084(0.740)
Centre	-0.387(0.665)	-0.389(0.664)	-0.132(0.692)
South	-0.710(0.703)	-0.668(0.690)	-0.544(0.731)
Age	-0.013(0.014)	-0.013(0.013)	-0.012(0.013)
DEA Efficiency	-0.020(0.016)	-0.020(0.016)	-0.022(0.018)
Manufacturing		*Benchmark*	
Energy Extraction	2.654***(0.875)	2.667***(0.893)	2.405***(0.885)
Non − financial Private Services	0.701(0.565)	0.719(0.565)	0.692(0.555)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.642(0.749)	-0.614(0.743)	-0.663(0.733)
Between 1/3 And 2/3 Of Turnover Exported	-0.601(0.968)	-0.551(0.960)	-0.610(0.955)
More Than 2/3 Of Turnover Exported	0.452(0.707)	0.456(0.711)	0.458(0.714)
Intercept	-3.516**(1.482)	-3.345**(1.511)	-4.364***(1.422)
	Odds ratio	Odds ratio	Odds ratio
Organized Crime Risk$_1$	1.471(0.873, 2.354)		
Organized Crime Risk$_2$		1.313(0.776, 2.086)	
Organized Crime Risk$_3$			2.253(1.349, 3.643)
Number of observations	1,090	1,090	1,087

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

TABLE 4.9: Ordered logit model with *Ordered Rationing* as dependent variable and *DEA Efficiency*.

Dependent variable	(1) *Ordered Rationing*	(2) *Ordered Rationing*	(3) *Ordered Rationing*
Independent variables			
Organized Crime Risk$_1$	0.261**(0.117)		
Organized Crime Risk$_2$		0.197*(0.117)	
Organized Crime Risk$_3$			0.326**(0.132)
Size	-0.115(0.077)	-0.124(0.077)	-0.121(0.076)
Northwest		*Benchmark*	
Northeast	-0.255(0.301)	-0.243(0.300)	-0.221(0.306)
Centre	-0.337(0.293)	-0.329(0.296)	-0.294(0.296)
South	-0.214(0.294)	-0.182(0.294)	-0.182(0.296)
Age	-0.009(0.006)	-0.009(0.006)	-0.008(0.006)
DEA Efficiency	-0.013*(0.007)	-0.013**(0.007)	-0.014**(0.007)
Manufacturing		Benchmark	
Energy Extraction	1.603***(0.491)	1.604***(0.496)	1.452***(0.496)
Non − financial Private Services	0.266(0.249)	0.269(0.249)	0.273(0.250)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.601**(0.276)	-0.608**(0.276)	-0.620**(0.278)
Between 1/3 And 2/3 Of Turnover Exported	-0.276(0.334)	-0.252(0.334)	-0.267(0.336)
More Than 2/3 Of Turnover Exported	0.039(0.308)	0.020(0.308)	0.027(0.309)
Cut1	1.479***(0.442)	1.386***(0.441)	1.562***(0.438)
Cut2	3.402***(0.481)	3.306***(0.480)	3.519***(0.482)
	Odds ratio	Odds ratio	Odds ratio
Organized Crime Risk$_1$	1.298(1.035, 1.614)		
Organized Crime Risk$_2$		1.218(0.974, 1.510)	
Organized Crime Risk$_3$			1.386(1.066, 1.781)
Number of observations	1,078	1,078	1,076

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Robust standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%. For odds ratios, confidence interval at 95% are reported.

with Balletta and Lavezzi (2023) conclusions regarding the regressive characteristics of extortion. Smaller enterprises, often experiencing elevated extortion rates, encounter difficulties in sustaining adequate liquidity and collateral, thereby amplifying their susceptibility in credit markets where banks perceive them as greater default risks.

Furthermore, the interaction between organized crime and credit conditions highlights overarching concerns of adverse selection and moral hazard. According to Bottoni et al. (2024), rising crime rates elevate financing costs, thereby exacerbating adverse selection as riskier firms pursue external funding. These findings support this, indicating that companies subjected to extortion or criminal threats experience more stringent credit conditions, thereby perpetuating the adverse selection cycle.

The increase in credit costs in high–crime areas, highlighted by Rodano (2021), demonstrates the broader effect of organized crime on judicial inefficiency. In areas where the judiciary is overburdened with criminal cases, civil proceedings, including bankruptcy, suffer significant delays. These delays create uncertainty for creditors, resulting in higher interest rates and stricter credit conditions, which supports the findings of this study.

Indeed, the perception of organized crime presence plays a crucial role in banks' behavior 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.

The 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.

From a policy standpoint, the evidence provided by empirical results suggests several complementary avenues of intervention. First, credit guarantee schemes could be explicitly targeted to firms operating in high–crime areas, by offering enhanced coverage ratios or reduced collateral requirements. This would compensate for the additional risk premium that private lenders tend to impose in crime–affected regions, addressing a market failure not linked to firm fundamentals but to external security conditions.

Second, the results point to a potentially measurable benefit from anti–crime enforcement policies in improving credit access. By reducing the expected incidence of extortion and intimidation, effective enforcement may not only enhance firms' operational security but also alter lenders' risk perceptions, thereby expanding credit supply. In this sense, crime prevention can generate indirect financial dividends, operating as a form of institutional investment that strengthens local credit markets.

Third, development banks and subsidized credit programs could play a pivotal role in compensating for the withdrawal of private finance from crime–affected territories. Targeted credit lines or co–lending arrangements could provide liquidity to viable but constrained firms, while maintaining appropriate monitoring standards to avoid moral hazard. Aligning such programs with regional enforcement initiatives would magnify their impact, ensuring that public credit complements – rather than substitutes – private lending.

Finally, policy efforts aimed at raising managerial and technical efficiency could further mitigate credit constraints, given the robust link between efficiency and credit access identified in the estimates.

Overall, an integrated strategy that combines security enforcement, targeted financial instruments, and productivity–enhancing interventions appears most promising for restoring equitable credit access in areas where organized crime undermines market functioning.

4.5 Concluding remarks

This study provides novel empirical evidence regarding the relationship between organized crime and credit rationing in Italy, elucidating how perceptions of criminal threats significantly affect firms' access to credit. The empirical analysis, based on a unique dataset from the Bank of Italy, demonstrates that the presence of organized crime imposes substantial constraints on firms. Specifically, extortion has the greatest impact on credit access, increasing the likelihood of credit rationing significantly more than other forms of criminal activity such as usury or the potential expropriation of a firm by criminal organisations. The perception of risk associated with criminal networks distorts market dynamics significantly, as banks become more cautious about lending practices due to threats of extortion and intimidation.

These results are consistent with prior research highlighting the detrimental effects of organized crime on economic performance and financial relationships. Organized crime creates an environment of uncertainty and risk, undermining the trust necessary for smooth financial transactions and increasing the perceived risk for banks. As a result, financial institutions adopt more stringent lending practices, raise interest rates, and require greater collateral, which disproportionately affects smaller firms that are often already burdened by higher extortion rates.

Furthermore, the findings support the existence of a vicious cycle of adverse selection and moral hazard in presence of high criminal activities, that forces firms to rely on riskier strategies and external financing due to higher credit costs and difficulty obtaining credit.

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. On the other hand, understanding the complex dynamics of credit rationing and its implications is crucial for both borrowers and lenders. The presence of organized crime may worsen credit supply due to increased risks and fears faced by firms.

Results contribute to the literature by extending the findings of Bonaccorsi di Patti (2009) and de la Miyar (2016), showing that the perception of organized crime presence makes credit access more difficult for firms.

Empirical findings suggest that banks should diversify their risk assessment models to better distinguish between firms vulnerable to crime–related risks and those that operate efficiently in high–crime areas. By refining these models, banks can mitigate overly conservative lending practices that might unjustly restrict credit to firms capable of thriving despite their challenging environments.

These outcome highlight the importance of integrating anti–crime measures into economic development policies. Improving credit access in organized crime–affected areas is critical for promoting business growth and reducing criminal networks' influence on the local economy. Targeted financial support and guarantee schemes can help mitigate perceived risks, enhancing credit availability in high–risk areas.

Beyond these considerations, the results also point to broader policy directions. Strengthening anti–crime enforcement can indirectly foster credit access by reducing extortion risk and restoring trust in local financial markets. At the same time, development banks and public credit programs could play a complementary role in supporting viable firms operating in high–crime areas, helping to offset private lenders' risk aversion. Such measures would be most effective if accompanied by initiatives that enhance firms' managerial capabilities and technological efficiency, which this study identifies as key factors mitigating credit constraints. Overall, coordinated actions that combine security enforcement, targeted financial instruments, and productivity–oriented support appear essential to reduce the distortive effects of organized crime on regional financial development.

Finally, these findings suggest several avenues for further research. Future studies could examine whether similar dynamics exist in other countries with different levels of organized crime, or the long–term effects of policy interventions aimed at reducing crime–related risks and improving firm credit access.

While this study provides valuable insights into the relationship between organized crime and credit rationing, it is important to acknowledge certain limitations that may affect the interpretation of the results. First, the assessment of organized crime presence is based on firms' subjective perceptions, which may introduce bias or variability in how the threat is perceived and reported. However, perception-based data have some advantages because they capture firms' real–time experiences and concerns, including situations in which formal complaints or legal actions may not be pursued due to fear of retaliation or mistrust in authorities. This enables to observe the impact of organized crime even in situations where official data may underestimate the problem. However, these findings should ideally be supported by empirical analyses of objective data, such as crime reports, judicial actions, or other official statistics. Future research could supplement this perception–based approach with objective measures to validate and strengthen the findings, providing a more complete picture of the investigated relationship.

Moreover, the applicability of these findings to other countries or regions with varying levels or types of criminal activity may be restricted by the fact that they are contingent upon the Italian context. Finally, while controlling for a range of firm characteristics, there may be other unobserved factors, such as local governance or specific anti–crime policies, that could also influence credit access in high-crime areas. Future research could address these limitations by employing longitudinal data to track changes in credit rationing over time.

Conclusions

This thesis has examined a set of internal and external determinants of banking efficiency and financial intermediation functioning through four empirical essays. Although each chapter addresses a specific research question–ranging from the role of efficiency in liquidity creation, to the impact of sustainability practices, to the influence of organized crime on bank efficiency and firms' access to credit–the essays collectively show that both internal managerial capabilities and external institutional and socio–economic conditions shape the performance of financial intermediaries and the allocation of credit within the economy. Collectively, the four essays advance the understanding of the determinants of banking efficiency by integrating these perspectives into a unified analytical framework that considers managerial efficiency, sustainability–oriented strategic choices, and adverse institutional environments such as crime and weak governance. This integrated perspective highlights the multifaceted nature of efficiency in modern banking systems.

Chapter 1 shows that banks' ability to create liquidity is significantly influenced by their technical efficiency. Using a Bayesian Stochastic Frontier Analysis, the study finds that optimal managerial practices, effective risk management, and the reduction of operational waste enhance banks' liquidity generation regardless of size or market structure. These results emphasize that internal drivers–rather than structural characteristics of the banking system–play a central role in shaping the primary function of financial intermediation.

Chapter 2 investigates whether adherence to the United Nations Environment Programme Finance Initiative's Principles for Responsible Banking affects banks' efficiency. The findings indicate that banks adopting these sustainability—oriented principles experience significant improvements in technical efficiency and, to some extent, in cost efficiency. The integration of ESG considerations into strategic and operational processes does not appear to impose a trade–off but rather contributes to strengthening banks' productive capacity, in line with a broader shift toward resilient and sustainability-oriented banking.

Chapter 3 examines the impact of organized crime on the efficiency of Italian cooperative banks. The empirical evidence shows that operating in areas with strong criminal presence significantly reduces both technical and cost efficiency. Criminal infiltration and local institutional weaknesses distort decision–making processes, governance mechanisms, and operational dynamics, making cooperative banks particularly vulnerable given their territorial focus and developmental role in local economies.

Chapter 4 extends the analysis to the demand side of credit markets, showing that perceived criminal activity–especially extortion–substantially increases the likelihood that firms face credit rationing. Banks respond to the heightened risk and uncertainty of criminal environments by tightening lending standards, which can exacerbate credit constraints in already disadvantaged areas. The study highlights a vicious cycle in which organized crime weakens banking efficiency and simultaneously restricts credit availability for firms operating in high–risk contexts.

Taken together, these studies offer an integrated view of the determinants of banking efficiency. Three overarching insights emerge. First, internal efficiency–shaped by managerial, organizational, and technological capabilities–plays a fundamental role in banks' intermediation capacity, affecting liquidity creation, resilience, and alignment with sustainability goals. Second, institutional and social conditions matter greatly: organized crime and institutional fragility can undermine efficiency and distort credit markets. Third, public policies and regulatory initiatives aimed at promoting sustainability show significant potential to simultaneously enhance social welfare and banking performance.

These findings give rise to several policy implications. Promoting advanced managerial practices and targeted training programs can strengthen banks' ability to create liquidity and support economic growth. Encouraging the adoption of sustainability frameworks such as the PRB may help align banks' environmental and social commitments with improvements in efficiency. At the same time, strengthening institutional frameworks and anti–crime measures is essential to prevent operational inefficiencies, credit restrictions, and systemic distortions in high–risk areas. These implications speak to different stakeholders–including bank managers, regulatory authorities, and local policymakers–highlighting the need for coordinated interventions across managerial, regulatory, and institutional domains.

Despite the contributions provided, this dissertation presents some limitations common to the four essays, including data availability constraints, the national focus of the analyses, and the challenge of capturing the dynamic evolution of phenomena such as ESG integration or criminal activity. Moreover, the periods examined coincide with regulatory and technological changes that may alter the observed relationships over time.

These limitations open several avenues for future research. Expanding the analysis to banking systems with different institutional settings would enrich the understanding of how contextual factors interact with efficiency. Examining the long–term effects of sustainability initiatives and the role of technological innovation could shed light on the structural determinants of efficiency in a rapidly evolving financial landscape. Additionally, combining subjective and objective measures of criminal activity would provide a more comprehensive picture of how crime affects both banking operations and firms' access to credit. Finally, studying the interaction between banking efficiency, public policies, and local socio–economic conditions over longer horizons could offer deeper insights into the mechanisms driving financial and regional development. Prioritizing these directions can help build a more comprehensive research agenda on banking efficiency, capable of capturing the interplay between firms, intermediaries, and institutional environments over time.

Overall, the dissertation shows that efficiency, sustainability, and institutional quality are deeply interconnected. Enhancing bank performance requires not only strong internal capabilities and responsible practices, but also supportive institutional and social environments. An integrated perspective on these dimensions is therefore essential for guiding public policies and banking strategies toward a more effective, sustainable, and resilient financial system.

Appendix A

Appendix – Chapter 1

A.1 System–Generalized Method of Moments

Dynamic panel estimators proposed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) are particularly suitable with "small T, large N" panels, which means that they are designed for panel with few time periods and many individuals. Furthermore, a linear functional form is assumed, with the dependent variable on the left–hand side influenced by its own past realizations. In addition, the model accounts for independent variables that are not strictly exogenous, includes fixed individual effects, and allows for heteroskedasticity and autocorrelation within individuals, but not across them (Roodman, 2009). Arellano–Bond estimation starts by transforming all regressors, usually by differencing, and uses the generalized method of moments (GMM) (Hansen, 1982). This is the so–called difference GMM. The Arellano–Bover/Blundell–Bond estimator augments the previous one by making an additional assumption that first differences of instrument variables are uncorrelated with the fixed effects. This allows the introduction of more instruments and can dramatically improve efficiency. It builds a system of two equations–the original equation and the transformed one–and is known as system–GMM.

Calculation of the GMM estimators can be based on a stacked system comprising all $(T-2)$ equations in first differences and the $(T-2)$ equations in levels corresponding to periods $3, \ldots, T$, for which instruments are observed. The instrument matrix for this system can be written as follows:

$$\mathbf{Z_i^+} = \begin{bmatrix} \mathbf{Z_i} & 0 & 0 & \ldots & 0 \\ 0 & \Delta y_{i2} & 0 & \ldots & 0 \\ 0 & 0 & \Delta y_{i3} & \ldots & 0 \\ . & . & . & \ldots & 0 \\ 0 & 0 & 0 & 0 & \Delta y_{i,T-1} \end{bmatrix} \tag{A.1}$$

where $\mathbf{Z_i}$ is defined as:

$$\mathbf{Z_i} = \begin{bmatrix} y_{i1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & \dots & 0 \\ . & . & . & \dots & . & \dots & . \\ 0 & 0 & 0 & \dots & y_{i1} & \dots & y_{i,T-2} \end{bmatrix} \tag{A.2}$$

In the context of SYS–GMM estimation, the validity of the model critically depends on two assumptions: the absence of serial correlation in the idiosyncratic error term, and the validity of the instruments used. These assumptions are typically assessed using the Arellano–Bond tests for autocorrelation (Arellano and Bond, 1991) and the Hansen test of overidentifying restrictions (Hansen, 1982). The Arellano–Bond tests examine whether the differenced residuals are serially correlated. Specifically, the test statistics for first-order (AR(1)) and second–order (AR(2)) serial correlation are computed based on the null hypothesis that no autocorrelation exists in the differenced residuals at order **m**. The null hypothesis is specified as follows:

$$\mathbf{H_0} : E[\Delta\epsilon_{i,t} \cdot \Delta\epsilon_{i,t-,}] = 0 \tag{A.3}$$

As expected, the AR(1) test usually rejects the null hypothesis due to the mechanical first–order autocorrelation introduced by differencing. However, failure to reject the null hypothesis in the AR(2) test is crucial: rejection would imply that the error term exhibits second–order autocorrelation, which would invalidate the use of lagged variables as instruments.

Additionally, the Hansen J test (an extension of the Sargan test that is robust to heteroskedasticity) evaluates the overall validity of the instruments by testing the null hypothesis that the instruments are uncorrelated with the error term and are correctly excluded from the estimated equation:

$$\mathbf{H_0} : \textit{The instruments are valid (exogenous)} \tag{A.4}$$

These diagnostic tests are essential for confirming the internal consistency of the GMM estimation framework. The combination of a significant AR(1), a non–significant AR(2), and a non–significant Hansen test supports the validity of the model specification and the chosen set of instruments.

TABLE A.1: Harris–Tzavalis unit root tests.

	Cat fat	*Cat fat*	*Cat nonfat*	*Cat nonfat*
	0.195*** (*0.000*)	0.207*** (*0.000*)	0.220*** (*0.000*)	0.236*** (*0.000*)
Cross–sectional means	Not removed	Removed	Not removed	Removed

Time trend is included in all tests. ***, ** and * represent respectively significance at 1%, 5% and 10%. Values in italics reported in parentheses are p–values.

A.2 Harris–Tzavalis unit–root test

To rule out the presence of a unit root in the *LC* variable, the Harris–Tzavalis unit–root test has been carried out. This test is particularly suitable for panels with large N and fixed T (Harris and Tzavalis, 1999). The Harris–Tzavalis test statistic relies on the OLS estimator, ρ, derived from the following regression model:

$$y_{it} = \rho y_{i,T-1} + \mathbf{z}'_{it}\gamma_i + \epsilon_{it} \tag{A.5}$$

where the term $\mathbf{z}'_{it}\gamma_i$ accounts for individual panel–specific means and trends. The test assumes that the error term ϵ_{it} is independent and identically distributed normal with constant variance across panels. The asymptotic distribution of the test statistic is established under the condition $N \to \infty$. The null hypothesis states that all panels exhibit a unit root, with the further assuming a common autoregressive parameter across panels. Table A.1 shows the results of the tests, which confirm that the variable is stationary.

Appendix B

Appendix – Chapter 2

B.1 Data Envelopment Analysis

Data Envelopment Analysis is a non–parametric mathematical programming approach originally introduced by Charnes et al. (1978). This methodology does not require assumptions about the distribution of the inefficiency term in the production or cost function. DEA models can be specified as either input– or output–oriented. In the former case, the objective of the Decision Making Unit (DMU) is to minimize inputs while maintaining the same output levels, whereas in the latter case the aim is to maximize outputs without changing the amount of inputs used.

In this robustness test, the impact of PRB and NZBA membership on bank efficiency is assessed using both input– and output–oriented models, following the two–stage procedure proposed by Simar and Wilson (2007) and assuming variable returns to scale (Banker et al., 1984). In the first stage of the two–stage DEA, inefficiency scores are obtained from a non–parametric frontier model. The second stage consists of regressing these scores on a set of covariates. Following Simar and Wilson (2007), 100 replications are used in the first loop to compute bias–corrected efficiency estimates, while 2,000 replications are used in the second loop to bootstrap the truncated regression model.

The input–oriented model under variable returns to scale is specified as follows:

$$\min_{\theta,\lambda_j} \theta \quad \text{subject to} \quad \begin{cases} \sum_{j=1}^{n} \lambda_j x_{i,j} \leq \theta\, x_{i,0}, & i = 1,\ldots,m, \\ \sum_{j=1}^{n} \lambda_j y_{r,j} \geq y_{r,0}, & r = 1,\ldots,s, \\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0, & j = 1,\ldots,n. \end{cases} \tag{B.1}$$

TABLE B.1: Two–stage input–oriented DEA.

	(1)	(2)
$ln(inefficiency)$		
PRB	-0.336(-0.413, -0.259)	
$NZBA$		-0.281(-0.401, -0.170)
GDP	-0.005(-0.012, 0.002)	-0.001(-0.008, 0.006)
$Inflation$	0.025(0.011, 0.038)	0.016(0.001, 0.029)
$Concentration$	-0.325(-0.578, -0.084)	-0.300(-0.560, -0.054)
$Intercept$	1.043(0.965, 1.125)	1.006(0.917, 1.090)

Number of observations: 1,922. Confidence intervals at 95% are reported in parentheses.

TABLE B.2: Two–stage output–oriented DEA.

	(1)	(2)
$ln(inefficiency)$		
PRB	-2.511(-2.814, -2.218)	
$NZBA$		-2.809(-3.281, -2.391)
GDP	0.018(-0.008, 0.045)	0.050(0.023, 0.079)
$Inflation$	0.183(0.130, 0.232)	0.141(0.090, 0.193)
$Concentration$	2.081(1.192, 2.938)	2.279(1.372, 3.181)
$Intercept$	4.037(3.730, 4.344)	3.756(3.437, 4.086)

Number of observations: 1,922. Confidence intervals at 95% are reported in parentheses.

The output–oriented model under variable returns to scale is specified as follows:

$$\max_{\varphi, \lambda_j} \varphi \quad \text{subject to} \quad \begin{cases} \sum_{j=1}^{n} \lambda_j x_{i,j} \leq x_{i,0}, & i = 1, \ldots, m, \\ \sum_{j=1}^{n} \lambda_j y_{r,j} \geq \varphi\, y_{r,0}, & r = 1, \ldots, s, \\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0, & j = 1, \ldots, n. \end{cases} \tag{B.2}$$

Table B.1 and Table B.2 report the empirical findings for the full sample, whereas Table B.3 and Table B.4 report results by bank size.

TABLE B.3: Two–stage input–oriented DEA by size.

	(1)	(2)	(3)	(4)
$ln(inefficiency)$				
PRB	-0.218(-0.349, -0.090)		-0.257(-0.321, -0.195)	
$NZBA$		-0.194(-0.400, -0.013)		-0.202(-0.280, -0.125)
GDP	-0.011(-0.021, -0.001)	-0.009(-0.019, 0.000)	0.004(-0.003, 0.010)	0.008(0.002, 0.015)
$Inflation$	0.004(-0.014, 0.022)	-0.000(-0.019, 0.018)	0.043(0.027, 0.058)	0.027(0.012, 0.042)
$Concentration$	-0.884(-1.216, -0.565)	-0.894(-1.233, -0.574)	0.337(0.046, 0.604)	0.334(0.050, 0.636)
$Intercept$	1.272(1.154, 1.387)	1.264(1.149, 1.376)	0.663(0.584, 0.746)	0.631(0.543, 0.719)
Number of observations	1,274	1,274	648	648

Confidence intervals at 95% are reported in parentheses. Models (1) and (2) refer to small banks, (3) and (4) refer to large banks.

TABLE B.4: Two–stage output–oriented DEA by size.

	(1)	(2)	(3)	(4)
$ln(inefficiency)$				
PRB	-1.449(-1.964, -0.961)		-0.714(-0.919, -0.499)	
$NZBA$		-1.920(-2.765, -1.196)		-1.026(-1.316, -0.764)
GDP	0.009(-0.025, 0.041)	0.020(-0.012, 0.053)	0.011(-0.011, 0.032)	0.031(0.008, 0.054)
$Inflation$	0.014(-0.049, 0.071)	0.003(-0.061, 0.062)	0.078(0.028, 0.131)	0.073(0.025, 0.124)
$Concentration$	-1.034(-2.112, -0.037)	-1.091(-2.150, -0.042)	-0.646(-1.701, 0.388)	-0.599(-1.688, 0.366)
$Intercept$	2.042(1.662, 2.432)	1.977(1.576, 2.355)	2.551(2.265, 2.844)	2.417(2.124, 2.746)
Number of observations	1,274	1,274	648	648

Confidence intervals at 95% are reported in parentheses. Models (1) and (2) refer to small banks, (3) and (4) refer to large banks.

Appendix C

Appendix – Chapter 4

C.1 Stochastic Frontier Analysis and perpetual inventory method

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

$$y_i = \alpha + x_i'\beta + \nu_i - \upsilon_i \tag{C.1}$$

where y_i represents the output of the *i*th 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:

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

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), the perpetual inventory method is applied and it is 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:

$$TE_i = \frac{E(y_i^*|u_i, x_i)}{E(y_i^*|u_i = 0, x_i)} \tag{C.3}$$

C.2 One–step Stochastic Frontier Analysis

To evaluate the impact of organized crime perceptions on firms' technical efficiency, a conventional two–stage mediation analysis cannot be implemented, since the inclusion of efficiency scores estimated via SFA in a second–stage model would produce biased estimates (Schmidt, 2011). The one–step approach overcomes this limitation by incorporating the perceptions of organized crime directly in the inefficiency term of the stochastic frontier (Battese and Coelli, 1995). The trans–log production function relies on the same output and inputs employed in the estimation of the efficiency scores, while the inefficiency equation is based on all the control variables included in logit and ordered logit models.

$$u_i = f(Organized\,Crime\,Risk_{ij},\ Size_i,\ Age_i,\ Geo\,Area_i,\ Macro\,Sector_i,\ Export_i) \tag{C.4}$$

Results of the one–step estimation, reported in Table C.1, confirm previous findings provided by Forgione and Migliardo (2023b).

TABLE C.1: One–step Stochastic Frontier Analysis.

	(1)	(2)	(3)
$\ln R_i$	0.690***(0.010)	0.690***(0.010)	0.691***(0.010)
$\ln L_i$	0.259***(0.013)	0.258***(0.013)	0.257***(0.013)
$\ln K_i$	0.040***(0.007)	0.040***(0.007)	0.040***(0.007)
$1/2(\ln R_i \times \ln L_i)$	-0.403***(0.013)	-0.402***(0.013)	-0.403***(0.013)
$1/2(\ln R_i \times \ln K_i)$	-0.019***(0.005)	-0.020***(0.005)	-0.020***(0.005)
$1/2(\ln L_i \times \ln K_i)$	0.020***(0.007)	0.021***(0.007)	0.021***(0.007)
$1/2(\ln R_i)^2$	0.200***(0.005)	0.201***(0.005)	0.201***(0.005)
$1/2(\ln L_i)^2$	0.200***(0.013)	0.198***(0.013)	0.198***(0.013)
$1/2(\ln K_i)^2$	0.006***(0.002)	0.006***(0.002)	0.006***(0.002)
Intercept	11.893***(0.015)	11.897***(0.015)	11.896***(0.015)
σ_v			
$Organized\ Crime\ Risk_1$	0.362***(0.096)		
$Organized\ Crime\ Risk_2$		0.263***(0.097)	
$Organized\ Crime\ Risk_3$			0.333***(0.114)
Size	0.221***(0.066)	0.194***(0.063)	0.190***(0.063)
Northwest		*Benchmark*	
Northeast	0.543(0.338)	0.535*(0.323)	0.506(0.326)
Centre	1.079***(0.322)	1.036***(0.306)	1.025***(0.308)
South	1.157***(0.326)	1.154***(0.311)	1.106***(0.312)
Age	-0.012***(0.004)	-0.011***(0.004)	-0.012***(0.004)
Manufacturing		Benchmark	
Energy Extraction	0.107(0.397)	0.053(0.390)	0.027(0.389)
Non − financial Private Services	0.976***(0.199)	0.963***(0.193)	0.954***(0.193)
Non − exporting Firm		*Benchmark*	
Less Than 1/3 Of Turnover Exported	-0.831***(0.212)	-0.810***(0.204)	-0.828***(0.207)
Between 1/3 And 2/3 Of Turnover Exported	-0.972***(0.312)	-0.924***(0.297)	-0.940***(0.299)
More Than 2/3 Of Turnover Exported	-1.317***(0.377)	-1.284***(0.359)	-1.281***(0.360)
Intercept	-4.931***(0.476)	-4.658***(0.445)	-4.666***(0.442)
Number of observations	2,333	2,331	2,328

Source: Bank of Italy, Survey on Industrial and Service Firms, [2009–2020]. Standard errors are reported in parentheses and are clustered at firm level, ***, ** and * represent respectively significance at 1%, 5% and 10%.

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