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**Italian Bank M&A: Assessing
Productive Efficiency in the Italian
Banking Sector**

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Abstract

This thesis investigates the cost efficiency of Italian banks during the consolidation wave of 2005–2024. Using Stochastic Frontier Analysis on a panel of 199 Italian banks, we estimate a normalised translog cost frontier following Evanoff and Örs (2008) and compare efficiency scores of banks absorbed through M&A against those remaining independently active. Dissolved banks operated 10.2 percent above the minimum-cost frontier on average, versus 5.9 percent for active banks - a robust gap of 4.2 percentage points. No bank exhibits economies of scale, while economies of scope reward portfolio diversification that dissolved banks, concentrated in lending, failed to capture. Cost efficiency and non-performing loan ratios are orthogonal, confirming that the two principal failure modes of Italian banking require separate policy responses.

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Chapter 1 - Introduction and Historical Consolidation Trends in The Italian Banking Sector

1.1 Research Motivation

Banking sector efficiency occupies a central role in modern economies because banks perform the essential function of financial intermediation: transforming savings into productive investment, allocating credit across households and firms, and transmitting monetary policy to the real economy. Inefficient banking systems therefore impose broader economic costs, including higher borrowing costs, weaker credit provision, lower profitability, and increased financial fragility. In highly bank-dependent economies such as Italy, where firms have historically relied more heavily on bank financing than capital markets, the efficiency of banks becomes particularly important for economic growth and financial stability.

One of the principal mechanisms through which banking systems attempt to improve efficiency is consolidation through mergers and acquisitions (M&A). The theoretical rationale for banking consolidation is grounded primarily in economies of scale and scope. Larger banking groups may spread fixed technological and regulatory costs across broader asset bases, improve diversification, strengthen bargaining power in funding markets, and generate synergies through branch rationalisation and workforce optimisation. M&A activity may therefore improve cost efficiency and enhance the long-run competitiveness of the banking sector.

However, the relationship between consolidation and efficiency is not unambiguously positive. Critics argue that larger banking groups may suffer from organisational complexity, bureaucratic inefficiencies, and agency problems that offset expected scale economies. Consolidation may also increase market concentration and reduce competitive pressure, allowing dominant institutions to exert market power rather than improve operational efficiency. The empirical literature consequently provides mixed evidence: while some studies identify meaningful post-merger efficiency gains, others find limited improvements or even deterioration in performance following consolidation.

These competing perspectives make the Italian banking sector a particularly valuable case study. Italy experienced one of the most extensive consolidation processes in Europe over the last three decades, transitioning from a highly fragmented and state-influenced system toward a more concentrated and market-oriented structure. At the same time, Italian banks faced severe stress during the Global Financial Crisis and the European Sovereign Debt Crisis, exposing

longstanding structural weaknesses including elevated operating costs, poor profitability, and exceptionally high levels of non-performing loans (NPLs).

Against this background, an important empirical question emerges: were the banks absorbed during Italy's consolidation wave genuinely less efficient than those that survived independently? Put differently, did consolidation effectively eliminate inefficient institutions and improve the overall efficiency of the sector, or did it merely reshape market structure without generating substantial operational gains?

This thesis addresses that question directly. Using Stochastic Frontier Analysis (SFA), modelled on the framework of Evanoff and Örs (2008), we estimate a normalised translog cost frontier for a panel of 199 Italian banks observed between 2005 and 2024. The analysis compares the cost efficiency scores of institutions subsequently dissolved through M&A against those that remained active. By providing bank-level evidence across both crisis and post-crisis periods, the study contributes to the broader debate on whether consolidation constitutes an effective mechanism for improving banking sector efficiency.

1.2 From Fragmentation to Consolidation (1990s–2015)

The Italian banking sector of the 1990s was structurally fragmented: over 900 institutions, mostly regional savings banks and cooperatives, operated with an average Return on Assets of 0.3% and a Cost-to-Income Ratio exceeding 70%, while roughly 70% of total assets remained under state control. The Amato-Carli Law (1990) and the Ciampi Law (1998) initiated privatisation and set the conditions for consolidation, which produced several landmark mergers: San Paolo–IMI and Credito Italiano–Unicredito in 1998, and the creation of Intesa Sanpaolo in 2007. Yet beneath these headline deals the long tail of small inefficient institutions persisted, and total branches and employees continued to rise through 2008 (Appendix, Tables 1.1; 1.2; 1.3).

The 2008 Global Financial Crisis and the 2010–2012 Sovereign Debt Crisis exposed those structural weaknesses in full. Emergency state interventions, €4 billion in hybrid capital and €250 billion in liability guarantees, accompanied a wave of forced M&A, while the NPL ratio climbed from 5.8% in 2008 to a peak of 17.1% in 2015 (Graph 1.1). Despite the damage, the crises acted as a catalyst: by 2015 operating bank numbers had fallen significantly and, for the first time, both branch counts and employee headcount began contracting, signalling the start of genuine cost discipline.

1.3 Strategic Consolidation and the Current M&A Wave (2016–Present)

Post-2016, ECB supervision under the Single Supervisory Mechanism and domestic reform, notably the 2016 decree consolidating Banche di Credito Cooperativo (from now on referred to as BCC) into holding groups, accelerated rationalisation. NPL ratios fell to 3.4% by 2023, branches declined at a 4.5% CAGR, and Return on Equity recovered materially. Today's M&A activity, including MPS's bid for Mediobanca, BPER's offer for Banca Popolare di Sondrio, and Banco BPM's acquisition of Anima Holding, is qualitatively different from its predecessors: strategically motivated and oriented toward scale, fee diversification, and cost reduction, even as the sector's Cost-to-Income Ratio remained above the EU average in 2023.

Chapter 2 - Literature Review

2.1 The Efficiency Hypothesis of Bank Mergers

The literature on bank mergers has historically been organised around two competing explanations for consolidation: the efficiency hypothesis, which holds that acquirers replace inefficient management and realise cost savings, and the market power hypothesis, which attributes consolidation to rent extraction rather than genuine efficiency gains. The distinction carries important policy implications. Berger and Humphrey (1992) provided the foundational empirical test of the efficiency hypothesis, concluding that cost improvements frequently failed to materialise in practice, due to managerial disruption and organisational inertia, although mergers where the acquirer held a clear efficiency advantage tended to produce better outcomes. This introduced the notion of the efficiency gap as a predictor of post-merger performance. DeYoung, Evanoff and Molyneux (2009) confirmed in a broad survey that frontier-based methods, and in particular Stochastic Frontier Analysis, were more successful in detecting efficiency gains than simple accounting indicators, especially in mergers involving poorly performing targets.

2.2 Banking Efficiency in Italy

Italy represents a particularly appropriate context for examining these dynamics. Weber (2017) demonstrated that Italian banks consistently reported operational expenditure ratios among the highest in the euro area, with cost-to-income ratios frequently exceeding 60 percent. With more than 600 credit institutions active in 2016, of which the majority were small BCC, the Italian system carried a structurally oversized branch network relative to the pace of digital transition

observed elsewhere in Europe. Jobst and Weber (2016) showed that for many of these institutions efficiency improvements were not simply desirable but constituted a precondition for financial viability, given the combination of compressed margins, elevated loan loss provisions, and persistent overhead costs. An additional complication noted in the literature, particularly in studies on the United States such as Avery and Samolyk (2003), is that consolidation may reduce relationship lending to small enterprises, a concern especially relevant in the Italian context after the 2016 reform of cooperative banks.

The methodological framework adopted in this study is Stochastic Frontier Analysis, introduced independently by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). The composite error term is decomposed into a symmetric noise component v and a one-sided inefficiency term u , where u represents systematic excess cost attributable to the firm. The signal-to-noise ratio $\lambda = \sigma_u / \sigma_v$ provides a diagnostic test of whether inefficiency dominates random variation. In our estimation, $\lambda = 3.752$ and the likelihood ratio test strongly rejects the null hypothesis of no inefficiency ($p < 0.001$), confirming that cost differences across Italian banks in the sample are predominantly structural rather than stochastic. Bank-specific efficiency scores are recovered following Jondrow et al. (1982) as $CE = \exp(E[u | \epsilon])$, with values above one indicating proportional excess cost relative to the estimated frontier. The cost frontier is specified as a translog function following Christensen, Jorgenson and Lau (1973), estimated under the intermediation approach of Sealey and Lindley (1977), which treats deposits as inputs and loans and securities as outputs. Linear homogeneity in input prices is imposed by normalising monetary variables by equity and expressing costs as a function of input price ratios.

The principal methodological reference for our specification is Evanoff and Örs (2008), who estimated a translog cost frontier for U.S. banks including three input prices, two outputs, and two netputs. The present study adapts this framework to the Italian data with two adjustments imposed by data availability: the price of labour is proxied by operating expenses over total assets rather than salaries per employee, and the two funding prices are aggregated into a single funding cost measure. These differences are summarised in Table 2.1. Despite these adaptations, the two studies share the same core framework and their results are therefore methodologically comparable.

Chapter 3 - Data and Methodology

3.1 Data Sources

Bank-level financial data come from Orbis Bank Focus (Moody's Analytics), the leading global database for financial institution data. The original dataset contains 63 variables and 552 bank-year observations covering the period 2005 to 2024. The dataset includes annual balance sheet, income statement, and regulatory capital data for Italian commercial banks, savings banks (Casse di Risparmio), and cooperative credit banks (Banche di Credito Cooperativo, hereafter BCC). After removing observations with missing values in the key SFA variables and requiring that total cost, total equity, and both input prices be strictly positive, the final estimation sample includes 525 bank-year observations from 199 Italian banks.

Banks classified as *Dissolved* (those subsequently absorbed through a merger or acquisition transaction) were observed in their last three available years before absorption, following the methodology of Evanoff and Örs (2008, Journal of Money, Credit and Banking). This window is designed to capture the pre-consolidation performance of the target institutions, ensuring that the estimated efficiency scores reflect the operational state of the bank in the period immediately preceding the consolidation event. Active banks were observed in their first three available years following the consolidation wave as a benchmark control group. Table 3.1 reports the full sample composition. Of the 525 observations retained in the estimation sample, 286 belong to 96 active banks and 239 belong to 103 dissolved banks. The sample includes both commercial banks, which account for 245 observations, and BCC and Casse di Risparmio, which account for 280 observations.

3.2 Variables Construction

Following the intermediation approach of Sealey and Lindley (1977), banks are treated as financial intermediaries that transform deposits and purchased funds into loans and financial securities, using labour and physical capital as inputs. Under this approach, deposits are treated as inputs rather than outputs, and the cost function captures the full resource cost of intermediation activity.

Total cost C is defined as the sum of interest expenses and operating expenses. This definition includes both the cost of funding (interest paid on deposits and borrowed funds) and the cost of operations (staff costs, depreciation, and administrative expenses), and therefore captures

the complete cost of intermediation in a way that is consistent across institutions of different size and business model.

Two input prices are included. The price of labour w_1 is measured as operating expenses divided by total assets, which serves as a proxy for the cost of human and organisational resources per unit of the bank's balance sheet. The price of funds w_2 is measured as interest expenses divided by total interest-bearing liabilities, capturing the average cost of the funding base. These two input prices are the standard choices in the banking efficiency literature following Berger and Mester (1997) and Evanoff and Örs (2008), and reflect the two primary categories of input costs for financial institutions.

Two output variables are included. The first output y_1 is securities plus interbank assets, representing the investment portfolio of the bank. The second output y_2 is net loans to customers, representing the traditional lending activity. Physical capital z_1 , measured as the book value of premises and fixed assets, enters the model as a fixed netput, a quasi-fixed input whose quantity is determined outside the short-run cost minimisation problem but which affects the position of the cost frontier. Equity capital z_2 serves as the normalisation variable, as described in Section 3.4. Table 3.2 provides descriptive statistics for all variables.

The decision to include two separate output measures, rather than a single aggregate of earning assets, follows the recommendation of Berger and Humphrey (1992) and Clark (1994) and is motivated by the substantial differences in resource intensity between loan production and securities investment. Loan production requires credit officers, relationship managers, monitoring capacity, and provisioning infrastructure, while maintaining a securities portfolio requires primarily a treasury function. Aggregating these two activities into a single output measure would obscure the cost structure of the institution and potentially bias the efficiency estimates.

3.4 The Translog Cost Function

The translog functional form is a second-order Taylor expansion of an arbitrary cost function in the logarithms of input prices and output quantities. Introduced by Christensen, Jorgenson and Lau (1973) and applied to banking by Berger and Humphrey (1992) and Berger and Mester (1997), the translog is a flexible functional form that imposes no a priori restrictions on the substitution elasticities or the returns to scale, making it well suited to a heterogeneous sample such as the Italian banking panel considered here. Its main advantage over the more restrictive Cobb-Douglas specification is that it allows the cost elasticities to vary freely across

observations, which is essential when the sample spans banks ranging from small rural cooperatives to large commercial institutions with total assets differing by a factor of several hundred.

The cost frontier estimated in this thesis takes the following form:

$$\begin{aligned}
(1) \quad \ln\left(\frac{C}{w_2 z_2}\right) = & \alpha_0 + \alpha_1 \ln\left(\frac{w_1}{w_2}\right) + \beta_1 \ln\left(\frac{y_1}{z_2}\right) + \beta_2 \ln\left(\frac{y_2}{z_2}\right) + \gamma_1 \ln\left(\frac{z_1}{z_2}\right) \\
& + \frac{1}{2} \alpha_{11} \left[\ln\left(\frac{w_1}{w_2}\right)\right]^2 + \frac{1}{2} \beta_{11} \left[\ln\left(\frac{y_1}{z_2}\right)\right]^2 + \frac{1}{2} \beta_{22} \left[\ln\left(\frac{y_2}{z_2}\right)\right]^2 + \frac{1}{2} \gamma_{11} \left[\ln\left(\frac{z_1}{z_2}\right)\right]^2 \\
& + \alpha_{12} \ln\left(\frac{w_1}{w_2}\right) \ln\left(\frac{y_1}{z_2}\right) + \alpha_{13} \ln\left(\frac{w_1}{w_2}\right) \ln\left(\frac{y_2}{z_2}\right) + \beta_{12} \ln\left(\frac{y_1}{z_2}\right) \ln\left(\frac{y_2}{z_2}\right) \\
& + \delta_1 \ln\left(\frac{w_1}{w_2}\right) \ln\left(\frac{z_1}{z_2}\right) + \delta_2 \ln\left(\frac{y_1}{z_2}\right) \ln\left(\frac{z_1}{z_2}\right) + \delta_3 \ln\left(\frac{y_2}{z_2}\right) \ln\left(\frac{z_1}{z_2}\right) \\
& + \sum_{t=2006}^{2024} \tau_t D_t + v_{it} + u_{it} \quad (1)
\end{aligned}$$

where all variables are as defined in Section 3.2, D_t are year binary variables equal to one for year t and zero otherwise, v_{it} is the symmetric noise component, and u_{it} is the one-sided cost inefficiency term. The model includes 14 structural parameters (one intercept, four first-order terms, four quadratic terms, and five cross-product terms), 19 year fixed effects, and one intercept, for a total of 34 parameters estimated on 525 observations.

3.5 Normalisation and Linear Homogeneity

All cost and output variables in equation (1) are normalised by the equity capital variable z_2 before taking logarithms, and the input prices are normalised by w_2 . This normalisation serves two purposes. First, it imposes linear homogeneity in input prices, a necessary condition for the cost function to be consistent with cost-minimising behaviour: if all input prices increase proportionally, total costs must increase by the same proportion. Dividing both C and w_1 by w_2 and expressing the dependent variable as $\ln(C/w_2 z_2)$ rather than $\ln C$ achieves this restriction without requiring any coefficient constraints on the estimated parameters. Second, normalisation by equity capital z_2 reduces heteroscedasticity arising from differences in scale across banks and ensures that the frontier reflects differences in efficiency rather than differences in financial leverage. Following Berger and Mester (1997), equity capital enters both as a normalisation variable and as a conditioning factor that accounts for the risk-taking behaviour of the institution.

3.6 The Composite Error Term and the SFA Estimator

The Stochastic Frontier Analysis methodology, introduced independently by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977), decomposes the residual of the cost function into two distinct components:

$$\varepsilon_{it} = v_{it} + u_{it} \quad (2)$$

The first component, v_{it} , is a symmetric two-sided disturbance that captures genuine random noise from measurement error, unobservable idiosyncratic shocks, and factors outside the control of the bank. It is assumed to follow a normal distribution:

$$v_{it} \sim \mathcal{N}(0, \sigma_v^2) \quad (3)$$

The second component, u_{it} , is a one-sided non-negative term that captures the excess cost incurred by a bank operating above the minimum-cost frontier, which is attributable to managerial inefficiency, suboptimal input combinations, and organisational slack. Under the half-normal specification, u_{it} is assumed to follow the absolute value of a normal distribution:

$$u_{it} \sim |\mathcal{N}(0, \sigma_u^2)|, \quad u_{it} \geq 0 \quad (4)$$

The two components are assumed to be mutually independent and independent of the regressors. The parameters of the model, including the structural coefficients of equation (1) and the variance parameters σ_u and σ_v , are estimated jointly by maximum likelihood using Stata's frontier command with options `cost dist(hnormal)`. Adding the inefficiency term to (rather than subtracting it from) the composite residual reflects the cost frontier convention: inefficiency raises costs above the minimum.

The model fit is assessed through two key diagnostics. The signal-to-noise ratio

$$\lambda = \frac{\sigma_u}{\sigma_v} \quad (5)$$

measures the relative importance of genuine inefficiency versus random noise in explaining the variation in observed costs. A value of λ substantially greater than one indicates that inefficiency is the dominant source of cost dispersion, validating the SFA approach over standard OLS. The null hypothesis that no inefficiency is present ($H_0: \sigma_u = 0$) is tested via a likelihood-ratio test comparing the SFA model against the restricted OLS specification; rejection of this null provides formal statistical support for the SFA framework.

3.7 Individual Efficiency Score Recovery

Since a direct estimate of the individual inefficiency term u_{it} cannot be derived from the composite residual ε_{it} alone, individual efficiency scores are recovered using the conditional expectation estimator of Jondrow, Lovell, Materov and Schmidt (1982). This estimator computes the expected value of u_{it} conditional on the observed composite error ε_{it} , and has become the standard approach in the SFA literature for deriving bank-level efficiency measures.

The cost efficiency score is then defined as:

$$CE_{it} = \exp(\hat{u}_{it}) \geq 1 \quad (6)$$

where $\hat{u}_{it}$ is the estimated inefficiency component. A score of $CE = 1$ indicates that the bank operates exactly on the efficient cost frontier, incurring the minimum achievable total cost for its given input prices, output mix, and fixed netput levels. A score of $CE = 1.10$ indicates that the bank's observed total costs are 10 percent above the minimum achievable level, which is entirely attributable to operational inefficiency rather than to random noise or to differences in the production environment. By construction, $CE \geq 1$ for all observations, and the distribution of efficiency scores is bounded below at unity with a right tail of varying length depending on the degree of heterogeneity in the sample.

This parameterisation is the standard convention for cost frontiers, as opposed to production frontiers where efficiency is defined as $TE = \exp(-\hat{u})$ and is bounded above by unity. The cost efficiency interpretation is straightforward: the reciprocal of CE gives the fraction of the bank's costs that would remain if it were to achieve full efficiency, while $CE - 1$ gives the proportional cost excess relative to the frontier.

3.8 Post-Estimation Analysis

After estimating the frontier and recovering individual efficiency scores, the analysis proceeds in several steps designed to characterise the distribution of efficiency across the sample and to test the central hypothesis of the thesis.

The first step is a comparison of mean efficiency scores between the dissolved and active groups, using both a parametric two-sample t -test and a non-parametric Wilcoxon-Mann-Whitney rank-sum test. The non-parametric test is included because the distribution of efficiency scores is known to be non-normal and right-skewed, which may limit the reliability of the parametric test in small subsamples. A statistically significant difference in mean

efficiency between the two groups, with dissolved banks exhibiting higher scores than active banks, would constitute evidence consistent with the efficiency hypothesis of bank mergers.

The second step disaggregates the efficiency scores by bank size quartile, using total assets as the size measure, and examines whether the dissolved-active efficiency differential is present at every level of the size distribution or is concentrated in particular size classes. This analysis is supplemented by a one-way ANOVA test of the null hypothesis that mean efficiency does not differ across size quartiles.

The third step compares efficiency scores across institutional types (commercial banks versus BCC and Casse di Risparmio), testing whether cooperative banks display systematically different efficiency levels from commercial institutions. This comparison is motivated by the institutional heterogeneity of the Italian banking sector and by the specific reform pressure placed on cooperative banks by the 2016 BCC governance reform.

Together, these analyses provide a comprehensive picture of the cost efficiency landscape of the Italian banking sector in the consolidation period, and form the empirical foundation for the results discussed in Chapter 4.

Chapter 4 - Empirical Results

This chapter presents the empirical results of the stochastic frontier analysis. The discussion is organised as follows. Section 4.1 reports the estimation of the cost frontier and assesses the model diagnostics. Section 4.2 compares the efficiency scores of dissolved and active banks, which constitutes the central finding of the thesis. Section 4.3 examines how efficiency varies across bank size quartiles. Section 4.4 investigates economies of scale and scope. Section 4.5 analyses the relationship between asset quality and cost efficiency. Section 4.6 traces the evolution of the efficiency gap across historical periods. Section 4.7 presents a battery of second stage regressions to identify the determinants of cost inefficiency. All graphs referenced in this chapter are reported in the Appendix.

4.1 Estimation of the Cost Frontier

The translog cost frontier specified in Chapter 3 is estimated by maximum likelihood using the half normal distributional assumption for the inefficiency term. The model converges after 10 iterations to a log likelihood of 731.46. Two diagnostic statistics confirm the validity of the

stochastic frontier approach. First, the likelihood ratio test comparing the SFA specification to the standard OLS model yields a chi squared statistic of 90.94 ($p < 0.001$), decisively rejecting the null hypothesis of no inefficiency in the composite error. Second, the estimated lambda, defined as the ratio of the standard deviation of inefficiency to the standard deviation of noise, equals 3.752. This indicates that the variation in the composite error is dominated by systematic cost inefficiency rather than by random noise. For comparison, Evanoff and Örs (2008) report lambda values of approximately 1.5 to 2.0 for their sample of U.S. commercial banks. The higher value in our sample likely reflects the greater heterogeneity of the Italian banking sector, which includes both large universal banks and very small cooperative institutions with fundamentally different cost structures.

Table 4.1 reports the key coefficients from the frontier estimation. All first order terms carry the expected positive signs and are statistically significant at the 1% level. The coefficient on the relative price of labour (0.870) indicates that a 1% increase in labour costs relative to funding costs raises total costs by approximately 0.87%. The output elasticities show that loans (0.615) are the costlier output to produce compared to securities (0.496), which is consistent with the labour intensive nature of credit origination, monitoring, and collection. Physical capital contributes modestly to costs (0.055). Among the second order terms, the cross term between the two outputs deserves particular attention: its coefficient is negative and highly significant (-0.164, $z = -21.24$), providing early evidence of economies of scope in the joint production of loans and securities, which we explore in detail in Section 4.4.

The year dummies reveal an interesting temporal pattern. The coefficients for 2013 to 2015 are negative, reflecting the post crisis cost compression as banks reduced operating expenses under regulatory and market pressure. The coefficients turn positive from 2020 onwards, with 2024 showing the largest upward shift (plus 0.204), capturing renewed cost pressures from inflation and the unwinding of extraordinary monetary policy measures.

4.2 Cost Efficiency: Dissolved versus Active Banks

Cost efficiency scores are recovered using the conditional expectation estimator of Jondrow et al. (1982), as described in Section 3.7. A score of 1.0 indicates that a bank operates exactly on the efficient cost frontier. Values above 1.0 indicate proportional cost excess: a score of 1.10 means the bank incurs costs 10% higher than what a fully efficient institution would spend to produce the same output mix at the same input prices.

Table 4.2 reports the distribution of efficiency scores for the full sample and for each status group. Across all 525 observations, the mean efficiency score is 1.079, indicating that the average Italian bank operates approximately 7.9% above the cost frontier. The median is lower at 1.054, reflecting the right skewed nature of the distribution: most banks cluster relatively close to the frontier, while a smaller number of highly inefficient institutions pull the mean upwards. The standard deviation of 0.070 confirms substantial heterogeneity in cost performance across the sample.

The central finding of the analysis is a statistically significant efficiency gap between the two groups. Active banks display a mean efficiency score of 1.059 (cost excess of 5.9%), while dissolved banks display a mean of 1.102 (cost excess of 10.2%). The difference of 4.2 percentage points is highly significant by both the parametric t test ($t = -7.19$, $p < 0.001$) and the non parametric Wilcoxon rank sum test ($z = -7.61$, $p < 0.001$). The dissolved group also exhibits nearly twice the standard deviation of the active group (0.087 versus 0.044), indicating that while some pre M&A banks were reasonably efficient, the group contained a long tail of severely underperforming institutions.

The overlapping histogram reported in Graph 4.1 (see Appendix) provides the clearest visual evidence of this result. Active banks are concentrated in a narrow band close to 1.0, with a sharp peak between 1.03 and 1.05. Dissolved banks display a much flatter and more spread out distribution extending well beyond 1.20, with several extreme outliers reaching 1.40 to 1.80. The overlap region between 1.00 and 1.10 shows that the most efficient dissolved banks were comparable to average active banks, but the long right tail demonstrates that the consolidation process disproportionately eliminated the least efficient institutions from the market.

An additional comparison by bank type reveals that BCC and Casse di Risparmio display slightly better cost efficiency than commercial banks (mean of 1.072 versus 1.086, $t = 2.367$, $p = 0.018$). This finding is consistent with the simpler business model of cooperative banks, which focus primarily on deposit taking and local lending and therefore require fewer complex and costly operations such as treasury management, trading, and advisory services. The difference amounts to approximately 1.4 percentage points and does not alter the dissolved versus active finding, which holds within both bank types.

4.3 Efficiency by Bank Size

To investigate the relationship between bank size and cost efficiency, we divide the sample into four quartiles based on total assets. Table 4.3 reports the mean efficiency scores by quartile

and by status. Q1 contains the smallest 25% of observations (132 banks, mean total assets of approximately €525 million), Q2 contains 131 observations (mean assets of €1.26 billion), Q3 a further 131 observations (mean assets of €2.72 billion), and Q4 the largest 131 observations (mean assets of €64.3 billion). The Q4 mean is heavily influenced by the presence of very large institutions such as UBI Banca.

The results reveal a non monotonic relationship between size and efficiency. The most efficient quartile is Q2 (mean of 1.054), followed by Q1 (1.069), Q3 (1.073), and Q4 (1.118). The ANOVA test rejects the null hypothesis of equal efficiency across quartiles with an F statistic of 23.06 ($p < 0.001$). Approximately 12% of the total variation in efficiency scores is explained by the size classification. The box plot in Graph 4.3 (see Appendix) illustrates this pattern: the Q2 box sits lowest on the vertical axis, while Q4 displays both the highest median and the widest dispersion.

This pattern suggests an optimal scale in the Italian banking system around the Q2 range, corresponding to institutions with total assets of approximately one to two billion euros. Banks in this class appear large enough to achieve basic operational economies but small enough to avoid the complexity costs that affect larger institutions, such as organisational overhead, legacy IT systems, and extended branch networks inherited from past mergers.

Crucially, the efficiency gap between dissolved and active banks persists within every size quartile. In Q1 the gap is 4.9 percentage points, in Q2 it narrows to 0.9 points, in Q3 and Q4 it is 3.3 points each. This confirms that the dissolved versus active efficiency differential documented in Section 4.2 is not an artifact of size: dissolved banks were less efficient than their active counterparts regardless of whether they were small local institutions or large commercial banks. The gap is smallest in Q2, the most efficient quartile, where even dissolved banks operated relatively close to the frontier, suggesting that mid size targets may have been acquired for strategic reasons such as geographic expansion rather than purely because of poor cost performance.

It is also worth noting how the composition of the sample shifts across quartiles. In Q1, there are 104 active observations but only 28 dissolved ones, meaning that most small banks in our sample remained independent. In Q4, the ratio reverses: only 31 active observations versus 100 dissolved. This suggests that the Italian consolidation wave primarily affected larger banks, which were absorbed into even larger groups.

4.4 Economies of Scale and Scope

The translog specification allows us to compute bank specific measures of scale and scope economies directly from the estimated coefficients. The Ray Average Cost Elasticity (EC) is defined as the sum of the partial derivatives of the log cost function with respect to each output (Table 4.4). When EC is below one, a proportional increase in all outputs raises total costs by less than proportionally, indicating economies of scale. When EC exceeds one, the bank faces diseconomies of scale. Because the translog is a flexible functional form, EC varies across observations depending on each bank's specific output mix and level.

The results are striking. No bank in the entire sample exhibits economies of scale. The minimum EC across all 525 observations is 1.026, still above unity. This means that for every Italian bank in our dataset, a proportional 1% increase in all outputs would raise total costs by approximately 1.11%. The scatter plot of EC against the logarithm of total assets, reported in Graph 4.4 (see Appendix), confirms this visually: all points sit above the red dashed line at $EC = 1$, and the trend line is essentially flat. Dissolved banks cluster higher, indicating more severe diseconomies.

The diseconomies intensify with bank size. Q1 banks have a mean EC of 1.101, while Q4 banks have a mean of 1.112, and the difference is significant ($t = -3.78$, $p < 0.001$). This means that larger banks face more severe cost penalties from output expansion than smaller ones, which is consistent with the finding in Section 4.3 that Q4 banks are the least cost efficient.

This finding has important implications for the consolidation debate. It suggests that the cost benefits of Italian banking M&A do not arise from scale economies. Making a bank bigger does not reduce its unit costs; if anything, it slightly increases them. The efficiency gains documented in Section 4.2 therefore arise from a different mechanism: the elimination of banks that were operating far above the cost frontier due to managerial or operational shortcomings, regardless of their size. This is consistent with the X efficiency hypothesis of Leibenstein (1966), which attributes cost differences across firms to managerial slack rather than to technological constraints.

In contrast to the scale result, we find strong evidence of economies of scope. The negative and highly significant cross term between the two outputs (coefficient of -0.164 , $z = -21.24$) indicates that the joint production of loans and securities is less costly than their separate production. Each additional unit of one output reduces the marginal cost of the other. The scope benefit, computed as the product of the negative cross term coefficient and the two output

levels, is significantly larger for active banks (mean of 0.334) than for dissolved banks (mean of 0.193). This difference is consistent with the observation that dissolved banks had a more concentrated output mix, with 72.2% of assets allocated to loans compared to 58.8% for active banks, and only 18.9% in securities versus 35.8% for active banks.

Taken together, the scale and scope results suggest that the economic rationale for consolidation does not lie in producing more output at lower unit cost. Rather, the efficiency gains come through scope: mergers that combine complementary output mixes, for instance a loan heavy target with a more diversified acquirer, can realise cost savings that neither institution could achieve independently. This result is consistent with the findings of Clark and Speaker (1994), who document similar patterns of limited scale economies but significant scope benefits in U.S. commercial banking using a generalised translog cost function.

4.5 The Relationship Between Asset Quality and Cost Efficiency

A common assumption in both the academic literature and among policy makers is that cost inefficiency and poor asset quality go hand in hand: banks that are poorly managed tend to make bad lending decisions, accumulate non performing loans, and simultaneously fail to control their operating costs. If this were the case, we would expect a strong positive correlation between NPL ratios and SFA cost efficiency scores.

The data tell a different story. As shown in Table 4.5, the pairwise correlation between cost efficiency and the NPL ratio is 0.017 with a p value of 0.71, which is essentially zero. Banks with high NPL ratios are not systematically less cost efficient, and banks that operate close to the cost frontier are not necessarily those with clean loan portfolios. The scatter plot in Graph 4.5 (see Appendix) illustrates this: the lowess trend line is nearly flat across the entire range of NPL ratios, and both active and dissolved banks are scattered without any visible pattern.

This result is confirmed in the multivariate setting. When we regress the inefficiency component on the NPL ratio, controlling for bank size, type, and dissolved status, the coefficient on the NPL ratio is 0.00003 with a t statistic of 0.12 ($p = 0.907$). The NPL variable adds no explanatory power. Meanwhile, the dissolved dummy remains strong and significant (coefficient 0.031, $t = 6.24$, $p < 0.001$), confirming that the efficiency gap between dissolved and active banks is not confounded by differences in asset quality.

Cost efficiency does correlate meaningfully with the cost to income ratio (0.277, $p < 0.001$), which is expected since CIR is itself a simpler measure of operational efficiency, and with return on average assets (-0.124, $p = 0.004$), indicating that more efficient banks tend to be

more profitable. The NPL ratio, on the other hand, is strongly correlated with profitability (-0.391 , $p < 0.001$), confirming that bad asset quality hurts the bottom line through provisions and write offs, but through a channel that is distinct from operational cost management.

This finding carries significant policy implications. The two main problems of the Italian banking sector during the sample period, the accumulation of non performing loans and the persistence of cost inefficiency, appear to have been largely independent phenomena requiring separate interventions. Addressing the NPL problem, as the ECB has emphasised through its guidance on non performing exposures, does not automatically solve cost inefficiency, and vice versa.

4.6 Temporal Analysis

To examine how efficiency evolved over time, we classify the sample into five historical periods corresponding to distinct phases of the Italian banking landscape: the pre crisis period (2005 to 2007), the financial and sovereign debt crisis (2008 to 2012), the post crisis years (2013 to 2015), the reform era (2016 to 2020), and the post COVID period (2021 to 2024). Table 4.6 reports the mean efficiency scores by period and status.

The efficiency gap between active and dissolved banks widens progressively over time, which is one of the most revealing findings of the analysis. During the financial crisis (2008 to 2012), the gap is only 1.5 percentage points. In the post crisis period (2013 to 2015), it increases to 4.8 percentage points. During the reform era (2016 to 2020), it reaches 6.7 percentage points. The box plot in Graph 4.6 (see Appendix) shows this pattern clearly, with the dissolved boxes shifting progressively upwards relative to the active boxes across periods.

This temporal pattern is consistent with the interpretation that regulatory reforms made the consolidation process progressively more selective. During the crisis years, M&A activity was driven largely by emergency interventions, involving both relatively efficient and less efficient banks. In the post crisis and reform periods, the regulatory push towards consolidation, particularly the 2015 Banche Popolari reform requiring transformation to joint stock companies and the 2016 BCC reform mandating consolidation into holding groups, accelerated the exit of the least efficient institutions specifically. The market and the regulators, in effect, became increasingly effective at identifying and removing the worst performers.

The post COVID period (2021 to 2024) shows a slight reversal, with the gap narrowing and even turning marginally negative. However, this period contains only 27 observations (3 active and 24 dissolved) and the result should not be given substantive weight. It may reflect specific

COVID related cost pressures that temporarily increased the efficiency scores of all banks, or it may simply be a consequence of the limited data available for the most recent years.

4.7 Determinants of Cost Efficiency

To formally identify the observable factors that explain variation in cost efficiency, we estimate six OLS regressions with robust standard errors, progressively adding control variables. The dependent variable is the cost efficiency score from the frontier estimation. Table 4.7 reports the results.

The baseline specification (Model 1) includes three structural variables: the dissolved dummy, the BCC dummy, and the logarithm of total assets. The dissolved dummy enters with a coefficient of 0.035 ($p < 0.001$), confirming that being a dissolved bank is associated with 3.5 additional percentage points of cost inefficiency after controlling for bank type and size. The BCC dummy is negative (-0.011), and bank size enters positively (0.008, $p < 0.001$), meaning that larger banks tend to be less efficient, consistent with the diseconomies of scale documented in Section 4.4.

Model 2 adds the interaction between dissolved and BCC status. The interaction coefficient is essentially zero (-0.001, $p = 0.906$), confirming that the consolidation effect operates equally across commercial banks and cooperative banks. Models 3 through 6 progressively add the NPL ratio, capitalisation variables (Tier 1 ratio and equity to assets), profitability (ROAA), and the cost elasticity measure. None of these variables achieves robust statistical significance once the dissolved dummy and bank size are controlled for.

Three conclusions emerge from this analysis. First, dissolved status is the most robust determinant of cost inefficiency across all six specifications. The coefficient ranges narrowly from 0.031 to 0.036 and is always significant at the 1% level, meaning that even after controlling for size, bank type, asset quality, capitalisation, and profitability, being a pre M&A target adds approximately 3 to 3.5 percentage points of cost excess above the frontier. Second, bank size is consistently associated with higher inefficiency in all models, confirming the structural cost disadvantage of large banks. Third, the dissolved coefficient barely changes as controls are added, from 0.035 in Model 1 to 0.035 in Model 6, indicating that it is not confounded by any observable bank characteristic. The R squared increases from 13.4% in the baseline to 18.1% in the full specification, suggesting that approximately 80% of the variation in cost efficiency is driven by unobservable factors such as management quality, organisational culture, technology choices, and internal governance.

Chapter 5 - Cost Structure Comparison

5.1 Why Cost Structure Matters

The previous chapters established that dissolved banks were significantly less efficient than active ones, that no meaningful economies of scale exist in our sample, and that economies of scope play an important role in keeping costs down. What those findings do not tell us, however, is why dissolved banks ended up on the wrong side of the frontier. The efficiency scores capture the distance from the best practice cost level, and the scale and scope results hint at possible mechanisms, but neither of them directly describes how the two groups of banks actually allocated their resources and structured their balance sheets.

This chapter fills that gap. By decomposing the cost and asset composition of each bank, we can observe the structural choices that ultimately translated into higher or lower efficiency. The logic is straightforward: if two groups of banks face broadly similar input prices (which our model controls for), then the differences in efficiency must come either from how they combine those inputs or from how they distribute their output across different activities. A bank that concentrates almost all of its assets in a single lending category is making a very different bet than one that spreads its portfolio between loans and securities, and that bet has direct consequences for the cost function.

We use four balance sheet ratios to capture this composition. On the cost side, we look at the interest expense share (interest expenses divided by total costs) and the operating expense share (operating expenses divided by total costs). These two shares sum to one, so they are mirror images of each other, but presenting both makes the comparison more intuitive. On the asset side, we look at the loan to assets ratio (net loans divided by total assets) and the securities to assets ratio (securities and interbank assets divided by total assets). Together, these four variables paint a reasonably complete picture of what each bank does with its money and how it pays for doing it. In addition to these four ratios, we also report the cost to income ratio (CIR), which is the single most widely used measure of operational efficiency in the banking industry and provides a useful benchmark for contextualising our results against the broader European literature.

The analysis proceeds in two steps. First, we compare BCC (cooperative credit banks) against commercial banks to verify that the two charter types are structurally similar enough to justify pooling them in a single frontier. This is not a minor technical point: if the two groups had

fundamentally different cost structures, our entire modelling approach would be questionable. Second, and more importantly, we compare active banks against dissolved banks to understand the balance sheet profile that characterised the institutions that eventually disappeared from the Italian banking system. We then connect these structural differences to the efficiency, scale, and scope results from the earlier chapters, building a complete narrative of why dissolved banks were more expensive to operate.

5.2 Cost Composition by Bank Type: BCC versus Commercial Banks

One potential concern with our single frontier approach is that BCC and commercial banks might operate with fundamentally different cost structures. If cooperative banks relied much more heavily on operating costs (because of their branch intensive, relationship based model) while commercial banks leaned on interest expenses (because of their greater reliance on wholesale funding), then pooling them into one cost function could distort the efficiency estimates. We would essentially be measuring the distance of cooperative banks from a frontier shaped predominantly by commercial bank technology, or vice versa, and interpreting the resulting gap as inefficiency when it is really just structural difference.

Table 5.1 addresses this concern directly by reporting the mean values of all four cost structure variables for BCC and commercial banks, along with the t statistic and p value from a two sample test of difference. The results are unambiguous. None of the four balance sheet ratios shows a statistically significant difference between the two groups. The p values range from 0.55 to 0.76, all well above any conventional significance threshold.

Starting with the cost side, the interest expense share is virtually identical at around 29 percent for both BCC and commercial banks, and the operating expense share sits at roughly 71 percent. These numbers mean that both types of institutions spend about two seven tenths total costs on staff, administration, depreciation, and other operating items, with the remaining three going to fund the interest they pay on deposits and borrowed money. The similarity is notable because one might have expected BCC, with their dense branch networks serving small communities, to have a significantly heavier operating cost burden. They do not. Whatever additional branch and staff costs they incur relative to their size appear to be offset by other efficiencies, or are simply not large enough to shift the aggregate ratio.

On the asset side, BCC devote about 64 percent of their assets to loans versus 65 percent for commercial banks, and the securities share is 29 versus 28 percent. Again, no meaningful difference. Both groups maintain a portfolio that is roughly 65 percent loans and 30 percent

securities, with the remaining 10 percent in other assets. Even the cost to income ratio, which captures overall operational efficiency in a single number, is statistically indistinguishable at 74 percent for BCC versus 72 percent for commercial banks.

This is an important validation result, and it is worth dwelling on its implications. Despite their very different governance structures (BCC are cooperatives with one member one vote rules, geographic constraints on operations, and strict limits on profit distribution, while commercial banks are shareholder owned with conventional corporate governance and no restrictions on where they can do business), the two types of institutions operate with essentially the same cost mix. They allocate similar proportions of their balance sheet to loans and securities, and they split their total costs between interest and operating expenses in almost identical ways.

This finding confirms that our decision to estimate a single stochastic frontier for the entire sample, rather than separate frontiers for each charter type, is methodologically sound. The underlying technology is shared; what differs across banks is how efficiently they use it. It also has a broader implication for the policy debate around cooperative banking in Italy. A recurring argument in the discussion around the 2016 BCC reform was that cooperative banks were structurally different institutions that needed to be assessed on their own terms. Our data suggest otherwise, at least when it comes to the cost function. BCC and commercial banks face the same input prices, produce the same outputs, and combine them in the same proportions. The differences in efficiency that we documented in earlier chapters are not driven by charter type. They are driven by something else entirely, and the next section identifies what that something is.

5.3 Cost Composition by Bank Status: Active versus Dissolved Banks

When we repeat the same decomposition exercise splitting the sample by bank status rather than charter type, the picture changes dramatically. Active and dissolved banks differ on every single dimension of cost structure, and the differences are both statistically significant and economically large. Table 5.2 (reported at the end of this chapter) presents the full comparison. Every row in the table is significant at the 0.1 percent level, which is a sharp contrast with the complete absence of differences we just observed between BCC and commercial banks. Let us work through the results one variable at a time.

Starting with the asset side, the most striking difference is in the loan to assets ratio. Dissolved banks had 72 percent of their assets concentrated in loans, compared to 59 percent for active banks. That is a gap of 13 percentage points ($t = -6.41$, $p < 0.001$). The mirror image appears

in the securities to assets ratio: dissolved banks held only 19 percent of their assets in securities and interbank positions, while active banks held 36 percent. In other words, dissolved banks were overwhelmingly pure lenders. They put nearly three quarters of everything they had into the loan book and kept very little in the way of diversification through securities or interbank lending. Active banks, by contrast, maintained a much more balanced portfolio, with a roughly 60/36 split between loans and securities that left room for diversification and, as we will see, for exploiting economies of scope.

This concentration has direct and measurable implications for the cost function. As we showed in Chapter 4, the translog coefficient on loans (y_2) is 0.615, while the coefficient on securities (y_1) is 0.496. Loans are the more expensive output to produce: each additional percentage point of lending activity pushes up costs by more than an equivalent increase in securities activity. A bank that is 72 percent loans and 19 percent securities is therefore operating in a region of the cost surface where marginal costs are higher than a bank with a 59/36 split. This is not necessarily about bad management or waste. It is, at least in part, a structural consequence of portfolio composition. A bank can be perfectly well managed and still face higher costs simply because the activity it specialises in is inherently more expensive.

Moving to the cost side, dissolved banks allocated 76 percent of their total costs to operating expenses and only 24 percent to interest expenses. Active banks showed a more balanced split of 67 percent operating and 33 percent interest. The gap of 9 percentage points in each direction is highly significant ($t = 5.82$ and -5.82 respectively, both with $p < 0.001$). This pattern reinforces and complements the asset side story. Banks that are heavily concentrated in lending need more staff, more branches, more loan officers, more credit analysts, and more back office infrastructure for processing and monitoring than banks that hold a significant share of their assets in securities. The cost of holding a government bond portfolio or maintaining interbank positions is primarily the interest you pay on the deposits or wholesale funding that finance them, and those show up as interest expenses. The cost of originating, underwriting, monitoring, restructuring, and collecting a large loan book is primarily the people and processes you need to do the actual lending, and those show up as operating expenses. So it is entirely consistent that dissolved banks, being pure lenders, would tilt their cost structure toward operating expenses and away from interest expenses. The two sides of the balance sheet tell the same story from different angles.

Finally, the cost to income ratio captures all of this in a single metric that is widely used and easily interpreted. Dissolved banks had an average CIR of 81 percent, meaning that for every euro of revenue they generated, 81 cents went to cover costs. Active banks had a CIR of 66 percent, a full 15 percentage points lower ($t = -8.17$, $p < 0.001$). To put this in perspective, the European Banking Authority generally considers a CIR above 70 percent to be a warning sign for bank viability, and the average for the euro area banking sector has hovered around 60 to 65 percent in recent years. The dissolved banks in our sample were well above the danger threshold, while active banks were right in line with the European average. This single number, perhaps more than any regression coefficient, captures the economic magnitude of the structural gap between the two groups.

5.4 Connecting Cost Structure to the Efficiency Results

The cost structure differences documented above do not exist in isolation. They connect directly to, and help explain, the three main empirical findings from the earlier chapters of this thesis. Making these connections explicit is important because it transforms a collection of separate statistical results into a coherent economic narrative.

The first connection is to the efficiency gap itself. In the Core Empirical Results chapter, we found that dissolved banks operate 10.2 percent above the cost frontier on average, compared to 5.9 percent for active banks, a difference of 4.2 percentage points that is significant at the 0.1 percent level. The cost structure data now reveals a plausible mechanism for this gap. Dissolved banks were concentrated in the highest marginal cost activity (lending), which meant they were operating in a steeper region of the cost surface where each additional unit of output cost more to produce. Even if they had been perfectly managed, their cost structure would have placed them at a disadvantage relative to more diversified peers. The 4.2 percentage point efficiency gap is therefore not purely a story about waste or mismanagement. It is partly, and perhaps substantially, a story about strategic positioning on the cost surface.

The second connection is to the economies of scope result. The Extended Analysis chapter showed that significant economies of scope exist in Italian banking, with the cross term on loans times securities equal to -0.164 ($z = -21.24$, $p < 0.001$). Producing loans and securities together is cheaper than producing them separately. But the magnitude of this benefit depends on how balanced a bank's output mix actually is. Active banks, with their 59/36 asset split, are well positioned to capture this joint production advantage. Their implied scope benefit, computed by evaluating the cross term at the group mean output shares, is 0.334. Dissolved

banks, with their lopsided 72/19 split, capture a scope benefit of only 0.193. Table 5.3 (at the end of this chapter) presents these numbers side by side. The difference is striking: active banks enjoy a scope benefit that is roughly 73 percent larger than what dissolved banks capture. This means that even before considering any differences in operational efficiency or management quality, the sheer composition of the balance sheet gave active banks a structural cost advantage that dissolved banks could not replicate without fundamentally changing their business model.

The third connection is to the cost output elasticity gap. We found that dissolved banks have a higher cost output elasticity (1.117 versus 1.099 for active banks, $p < 0.001$), meaning that when dissolved banks grow their output by 10 percent, their costs grow by 11.17 percent, while active banks see costs grow by 10.99 percent for the same output increase. The cost structure data explains why. Because dissolved banks were concentrated in lending, which carries the higher first order cost coefficient (0.615 for loans versus 0.496 for securities), their total cost output elasticity is mechanically pulled upward. They were not just inefficient in the sense of being above the frontier. They were also operating in a part of the cost surface where each incremental euro of output was more expensive to produce. Growth, for these banks, did not bring cost relief. If anything, it made the problem worse.

Figure 5.3 illustrates the relationship between loan concentration and cost inefficiency visually. The positive association is visible for both groups, but dissolved banks cluster much more tightly in the upper right corner of the scatter plot: high loan share and high cost efficiency scores (meaning further from the frontier). Active banks are more spread out, with many observations in the lower left region where diversification is higher and inefficiency is lower. The visual pattern is consistent with the statistical results and reinforces the interpretation that portfolio composition is a key driver of the efficiency gap.

5.5 The Full Picture

Pulling together all the pieces, a coherent narrative emerges about the structural differences between the banks that survived the Italian consolidation wave and those that did not.

Dissolved banks were, first and foremost, pure lenders. They had nearly three quarters of their assets in the loan book and less than a fifth in securities. This concentration meant they could not benefit from the economies of scope that reduce costs for banks with a more balanced output mix. It also meant they were operating in the region of the cost surface where marginal costs are highest, since the translog model shows that loans are the more expensive of the two outputs to produce. On the cost side, their heavy lending orientation translated into a structure

dominated by operating expenses (76 percent of total costs, versus 67 percent for active banks). This is consistent with the labour intensive nature of lending: originating, underwriting, monitoring, and collecting loans requires people and processes that show up as operating costs, while securities holdings generate returns with relatively lower operational overhead and their financing costs appear primarily as interest expenses.

Table 5.3 brings all of the key metrics together in a single summary, presenting the cost structure ratios alongside the efficiency and elasticity measures from earlier chapters. The contrast is unmistakable across every dimension.

It is important to note what this analysis does not say. We are not claiming that lending concentration caused these banks to fail. Many of the dissolved institutions were liquidated, merged, or resolved for reasons that go well beyond cost efficiency: governance failures, excessive exposure to non performing loans, fraud in some cases, or simply the strategic decision of an acquiring bank to absorb a smaller competitor. What the cost structure data does tell us is that the banks which ended up disappearing were operating with a balance sheet profile that made them structurally more expensive to run, even before accounting for any managerial inefficiency. Their concentration in lending was not just a business strategy. It was a vulnerability.

This finding also speaks to the question of what consolidation actually achieves. The conventional narrative around Italian banking mergers often frames them as a response to asset quality problems, with non performing loans as the main villain. Our data suggest that a second, equally important dimension was at play: cost structure. The banks that disappeared were not just those with bad loan books. They were those whose entire operating model, built around concentrated lending with minimal diversification, placed them at a permanent cost disadvantage relative to their more balanced peers. The consolidation wave, whatever its proximate triggers, ended up removing precisely the institutions whose cost structure was least sustainable in a competitive banking environment.

One final observation ties this chapter back to the BCC versus commercial comparison with which we began. The fact that charter type produces no structural differences while bank status produces enormous ones tells us something important about what matters in Italian banking. Governance form, whether cooperative or shareholder owned, is essentially irrelevant to the cost function. What matters is the strategic choice of how to deploy assets and, consequently, what kind of cost base a bank builds around that deployment. Dissolved banks, regardless of

whether they were BCC or commercial, made the same bet on concentrated lending, and that bet left them exposed when the cost environment shifted. Active banks, again regardless of charter type, maintained more diversified portfolios that gave them access to scope economies and a more balanced cost structure. The lesson, if there is one, is that the real dividing line in Italian banking was never between cooperatives and commercial banks. It was between diversified institutions and pure lenders.

Chapter 6 - Additional Analyses

This chapter presents two supplementary analyses that complement the core findings discussed in the preceding chapters. The first is a robustness check that replaces the distributional assumption imposed on the inefficiency term, and the second is a comprehensive ranking of individual banks by their average cost efficiency scores. Together, these exercises reinforce the validity of the main results and offer additional insight into the heterogeneity of the Italian banking sector.

6.1 Robustness Check: Exponential Distribution

A well known concern in stochastic frontier analysis is that the estimated efficiency scores may be sensitive to the assumed distribution of the one sided error component. Our baseline model imposes a half normal distribution on the inefficiency term u , which constrains most of the probability mass near zero and implies that the majority of banks operate relatively close to the efficient frontier. While this is the most commonly adopted assumption in the literature, it is not the only plausible one. To assess whether our findings depend on this particular choice, we re estimate the full translog cost frontier using an exponential distribution for u , which features a heavier right tail and permits a larger proportion of moderately inefficient observations.

The exponential model converges without difficulty and produces a log likelihood of 762.89, compared to 731.46 for the half normal specification. This improvement in fit is expected, as the exponential distribution is less restrictive in the shape of the inefficiency density and can therefore accommodate a wider range of inefficiency patterns. Both models are strongly significant overall, with Wald chi squared statistics well above the critical values, and the estimated cost frontier coefficients are virtually identical across the two specifications. The first order output elasticities, the input price coefficient, and the cross terms all retain the same

signs, magnitudes, and significance levels. This confirms that the underlying technology parameters of the translog cost function are not driven by the distributional choice.

Table 6.1 reports the key comparison between the two models. The exponential specification produces slightly lower average efficiency scores across the board, as is typical when moving from a half normal to a distribution with a thicker tail. The overall sample mean under the exponential model is 1.061, meaning the average bank operates 6.1% above the cost frontier, compared to 1.079 (7.9% above) under the half normal. Active banks average 1.046 under the exponential model versus 1.059 under the half normal, and dissolved banks average 1.080 versus 1.102. More importantly for our purposes, the gap between dissolved and active banks is preserved under the alternative specification: the difference is 3.5 percentage points under the exponential model, compared to 4.2 percentage points under the half normal, and it remains highly significant in both cases ($t = -5.57$, $p < 0.001$ for the exponential; $t = -7.19$, $p < 0.001$ for the half normal). The direction, magnitude, and statistical significance of the central finding are therefore unchanged.

To further confirm the consistency of the two sets of scores, we compute the Pearson correlation coefficient between the bank level efficiency estimates obtained from the half normal and exponential models. The correlation is 0.974 ($p < 0.001$), indicating near perfect agreement in the ordering of banks. This means that a bank classified as highly efficient under one distributional assumption is classified in essentially the same way under the other. This result is consistent with the observation made by Evanoff and Örs (2008), who note that while the absolute levels of cost efficiency may differ depending on the distributional assumption, the rankings of banks remain stable across specifications. Bauer et al. (1998) reach a similar conclusion in a broader methodological comparison. Our findings thus confirm that the conclusions drawn in the preceding chapters, in particular the significant efficiency gap between dissolved and active banks, the absence of meaningful scale economies, and the independence between cost efficiency and non performing loan ratios, are all robust to the choice of the inefficiency distribution.

6.2 Bank Efficiency Rankings

To complement the aggregate statistical analysis, we collapse the panel to bank level averages and rank all institutions in the sample by their mean cost efficiency score over the observed period. This exercise serves two purposes. First, it provides a direct validation of the SFA estimates against well known episodes in Italian banking history, allowing us to verify whether

the model assigns low efficiency to banks that were widely recognized as underperforming. Second, it illustrates the heterogeneity that exists within both the dissolved and active groups, revealing that the relationship between efficiency and consolidation outcomes is not deterministic.

Table 6.2 reports the ten most efficient banks in the sample. The top ranked institution is Banca di Valle Camonica, a small cooperative bank based in Lombardy that was eventually absorbed through M&A, operating on average just 1.3% above the cost frontier. The composition of this group is noteworthy. It includes five dissolved banks and five active banks, indicating that consolidation in the Italian sector was not exclusively targeted at inefficient institutions. Some highly efficient banks were absorbed for strategic reasons unrelated to their cost performance, such as geographic complementarity, the desire of acquiring institutions to expand their branch network, or the need to achieve regulatory capital thresholds in the aftermath of the European Banking Union.

Table 6.3 reports the ten least efficient banks. The contrast with the top group is stark: eight of the ten are dissolved, and several correspond to the most prominent consolidation episodes in recent Italian banking history. UBI Banca, which was absorbed by Intesa Sanpaolo in 2020 as part of one of the largest domestic banking deals of the decade, operated on average 27% above the cost frontier despite being one of the largest banks in Italy by total assets (approximately €149 billion). Banca Popolare di Vicenza, placed into compulsory liquidation in 2017 following the failure of two capital increases and the discovery of widespread governance irregularities, was roughly 20% above the frontier. The Cassa di Risparmio di Cesena and Nuova Cassa di Risparmio di Ferrara, both resolved or restructured during the Italian banking crisis of 2015 to 2017, also appear in the bottom ten with efficiency scores exceeding 1.20. The presence of these well known cases at the bottom of the ranking provides strong external validation for the SFA estimates and confirms that the model captures meaningful variation in bank level cost performance. Among the two active banks that appear in the bottom ten, Cassa Centrale Raiffeisen and Banca Stabiese, both are relatively small institutions operating in niche markets. Their presence suggests that while dissolution has historically been associated with inefficiency, there remain pockets of underperformance among surviving banks that have not yet been addressed by the consolidation process. A particularly instructive case is that of Banca delle Marche, which ranks as the second most cost efficient bank in the entire sample at just 1.5% above the frontier. This bank was one of the four institutions resolved by the Italian government in November 2015 under the newly introduced Bank Recovery and Resolution

Directive (BRRD) framework, alongside Banca Etruria, Cassa di Risparmio di Ferrara, and CariChieti. Its failure was driven by a catastrophic deterioration in asset quality, with non performing loans rising to unsustainable levels, compounded by serious governance failures. Crucially, these problems had nothing to do with an inability to control operating costs. The SFA model correctly identifies Banca delle Marche as a highly efficient institution in terms of cost management, a finding that vividly illustrates the independence between cost efficiency and balance sheet risk documented in Chapter 5. A bank can operate very close to the efficient cost frontier and still fail if its loan portfolio collapses. This distinction between operational efficiency and credit risk is central to understanding why some banks were resolved despite appearing well managed on the cost side.

In summary, the bank level rankings confirm that the dissolved group was, on average, significantly less cost efficient than the active group, but they also reveal important exceptions that enrich the interpretation of the aggregate results. Consolidation in the Italian banking sector has been driven by a combination of cost inefficiency, strategic considerations, and, in some cases, balance sheet vulnerabilities that are uncorrelated to operational performance.

Chapter 7 - Conclusion

The analysis shows that dissolved banks operated on average 10.2 percent above the minimum cost frontier in the years preceding their absorption, compared to 5.9 percent for banks that remained independent. This difference of 4.2 percentage points is statistically decisive and survives alternative distributional assumptions, size controls, differences in asset quality, and bank type. It also widened progressively across successive regulatory regimes, from 1.5 percentage points during the financial crisis to 6.7 points during the reform era, suggesting that consolidation became increasingly targeted and selective over time.

Two structural findings enrich this result. The first is the complete absence of scale economies across the entire sample. Every bank exhibits a cost elasticity above unity, meaning that growing a bank does not reduce its unit costs — removing a badly managed one does. This places the efficiency gain within the X efficiency framework of Leibenstein rather than any technological advantage linked to size. The second finding concerns economies of scope. Dissolved banks were unable to capture the joint production benefits available to more

diversified peers. With nearly three quarters of their assets concentrated in lending, they operated in the most expensive region of the cost surface, while active banks maintained a more balanced portfolio and enjoyed a scope benefit approximately 73 percent larger.

Perhaps the most important result from a policy perspective is the independence between cost efficiency and asset quality. The correlation between SFA scores and the NPL ratio is essentially zero across all specifications. Cost inefficiency and credit risk are two separate failure modes requiring two separate policy responses — treating them as a single problem risks directing supervisory attention toward the wrong targets.

Taken together, the results offer a coherent and empirically supported reading of the Italian banking consolidation wave. The institutions that disappeared were structurally more expensive to operate, less diversified in their output mix, and progressively less able to remain competitive as the cost environment became more demanding. The consolidation process, whatever its immediate causes, ended up doing exactly what the efficiency hypothesis predicts it should do.

APPENDIX

Chapter 1

Indicator	2000	2004	2008
Number of Banks	820	760	790
Bank Branches	26,000	29,000	34,500
Employees	310,000	325,000	332,000
NPL Ratio (%)	7.20	6.00	5.80
Return on Equity (%)	6.50	7.00	5.70
Cost-to-Income Ratio (%)	70	68	66
Tier 1 Capital Ratio (%)	8.00	8.50	9.00

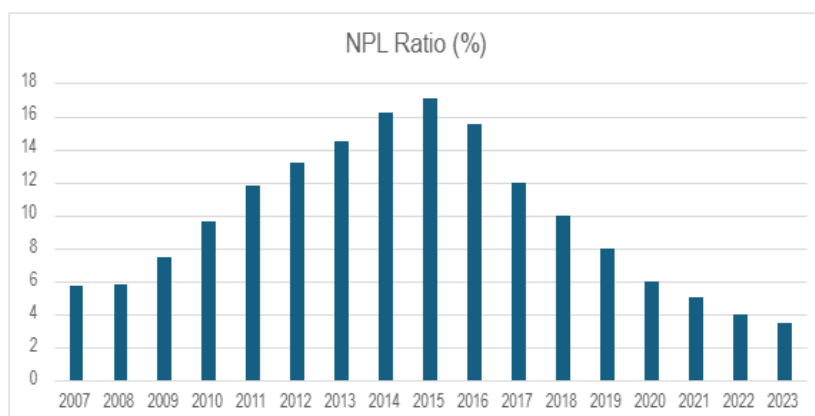
Table 1.1 Selected data regarding the Italian Banking Industry. The number of banks was rounded up to the nearest 10th, the number of total branches to the nearest 500th and the number of employees to the nearest 1000th.

Year	2008	2009	2010	2011	2012	2013	2014	2015
Number of Banks	790	770	750	710	690	670	650	620
Bank Branches	34,5	34,2	34	33	32	31,5	30,5	30
Employees	332	331	330	325	320	317	314	310
ROE (%)	3.2	2	1	0.5	-0.8	-1.5	-2	-2
Cost-to-Income (%)	66	67	68	69	70	71	70	70
Tier 1 Capital Ratio (%)	9	9.2	9.5	10.5	11	11.5	11.8	12.3

Table 1.2 Selected data regarding the Italian Banking Industry.

Year	2016	2017	2018	2019	2020	2021	2022	2023
Number of Banks	580	540	510	480	460	450	450	440
Bank Branches	29	27	25,5	24	23	21,5	20,5	20
Employees	305	295	290	285	280	270	265	260
ROE (%)	0	1.5	3	4	4	5.5	6	6.5
Cost-to-Income (%)	68	66	64	63	62	60	59	58

Table 1.3 Selected data regarding the Italian Banking Industry.



Graph 1.1 Non-Performing Loans Ratio (2007-2023) in Italy.

Chapter 2

Variable	Role	Evanoff & Örs (2008)	Caselli & Mozzicato
Total Cost (C)	Dependent variable	Interest + non-interest expenses	Interest + non-interest expenses
Output 1 (y_1)	Output	Total loans	Total loans
Output 2 (y_2)	Output	Securities	Securities
Input price 1 (w_1)	Labour price	Salaries / headcount	Operating expenses / total assets
Input price 2 (w_2)	Deposit funding	Interest on deposits / deposits	Aggregate funding cost
Input price 3 (w_3)	Borrowed funds	Interest on borrowings / borrowings	(Merged into w_2)
Netput 1 (z_1)	Fixed netput	Off-balance-sheet items	Off-balance-sheet items
Netput 2 (z_2)	Normalising netput	Equity	Equity

Table 2.1 Variable Mapping: Evanoff & Örs (2008) vs. Caselli & Mozzicato

Chapter 3

Group	Banks	Observations	Notes
Active (post-consolidation control)	96	286	Non-merging institutions; observed in first 3 years post-consolidation
Dissolved (pre-M&A targets)	103	239	Banks absorbed via M&A; observed in last 3 years before absorption
In Liquidation (excluded)	18	54	Excluded from main SFA estimation
Full estimation sample	199	525	Active + Dissolved; balanced three-period panel

Table 3.1 Sample Composition; data sourced from Orbis BankFocus (Moody's Analytics). The three-period observation window follows the design of Evanoff and Örs (2008). In-liquidation institutions are excluded because their cost behaviour during wind-down is unlikely to reflect normal operating decisions.

Variable	Definition	Mean	Std. Dev.	Min	Max
Total Cost C (EUR m)	Interest expenses + operating expenses	312.4	1,847.2	28.6	5,104.3
Price of Labour w_1	Operating expenses / Total assets	0.041	0.018	0.011	0.093
Price of Funds w_2	Interest expenses / Total interest-bearing liabilities	0.018	0.009	0.003	0.048
Securities & Interbank y_1 (EUR m)	Securities + interbank assets	4,435	28,513	1.01	406,493
Net Loans y_2 (EUR m)	Net loans to customers	10,024	55,285	0.43	839,849
Physical Capital z_1 (EUR m)	Book value of premises and fixed assets	180.4	1,083	5.3	17,477
Equity z_2 (EUR m)	Total equity (normalisation variable)	1,117	6,205	-1,526	91,909
Total Assets (EUR m)	Balance-sheet total	4,218	16.9	201	7,431
Cost-to-Income Ratio (%)	Total costs / Operating income	73.0	35.7	31.1	944.
NPL Ratio (%)	Non-performing loans / Total loans	15.6	9.3	0.2	61.4
ROAA (%)	Return on average assets	-0.08	1.21	-8.4	3.2

Table 3.2 Descriptive Statistics (N = 525 bank-year observations); monetary variables in millions of euros. w_1 and w_2 are unit-free ratios. Statistics computed over the full estimation sample of 525 bank-year observations (286 active, 239 dissolved). Source: Orbis BankFocus (Moody's Analytics).

Chapter 4

Variable	Coeff.	z-stat	p-value	Interpretation
$\ln(w_1/w_2)$	0.870	54.61	<0.001	Labour cost elasticity
$\ln(y_1/z_2)$	0.496	22.27	<0.001	Securities output elasticity
$\ln(y_2/z_2)$	0.615	22.09	<0.001	Loan output elasticity
$\ln(z_1/z_2)$	0.055	3.59	<0.001	Physical capital
$\ln(y_1) \times \ln(y_2)$	-0.164	-21.24	<0.001	Scope cross-term

Table 4.1 Key Estimated Coefficients from the Translog Cost Frontier Notes: Selected first-order and cross-product terms from the translog cost frontier. Full estimation output with all 14 structural parameters and year dummies is available upon request. Model estimated on 525 observations by maximum likelihood; log-likelihood = 731.46, $\lambda = 3.752$, LR test $\chi^2 = 90.94$ ($p < 0.001$).

Statistic	All Banks	Active	Dissolved	Difference
N	525	286	239	
Mean	1.079	1.059	1.102	4.2 pp
Median	1.054	1.045	1.086	4.1 pp
Std. Dev.	0.070	0.044	0.087	
P25	1.038	1.035	1.045	
P75	1.100	1.073	1.129	
Min	1.007	1.007	1.010	
Max	1.814	1.249	1.814	
t-test				$t = -7.19^{***}$

Table 4.2 Distribution of Cost Efficiency Scores Notes: Cost efficiency scores computed as $CE = E[\exp(u)|\varepsilon]$ following Jondrow et al. (1982). A score of 1.0 = operation on the frontier; values above 1.0 = proportional cost excess. *** denotes significance at the 1% level. The t-test is a two-sample test with unequal variances; the Wilcoxon is a non-parametric rank-sum test.

Quartile	Mean TA (€m)	N	Active	Dissolved	Gap (pp)	Overall
Q1 (Small)	525	132	1.058	1.107	4.9	1.069
Q2	1,264	131	1.051	1.060	0.9	1.054
Q3	2,724	131	1.056	1.089	3.3	1.073
Q4 (Large)	64,3	131	1.093	1.126	3.3	1.118
Total		525	1.060	1.102	4.2	1.079

Table 4.3 Cost Efficiency by Size Quartile and Bank Status Notes: Size quartiles defined on total assets. Gap = dissolved mean minus active mean. ANOVA F-statistic = 23.06 ($p < 0.001$). Bartlett's test for equal variances: $\chi^2(3) = 138.65$, $p < 0.001$.

Group	N	Mean EC	Std. Dev.	Interpretation
All banks	525	1.107	0.021	Mild diseconomies of scale
Active	286	1.099	0.014	
Dissolved	239	1.117	0.024	Stronger diseconomies
Q1 (Small)	132	1.101	0.019	
Q4 (Large)	131	1.112	0.027	$t = -3.78$, $p < 0.001$

Table 4.4 Ray Average Cost Elasticity (Economies of Scale) Notes: $EC = \partial \ln(C) / \partial \ln(y_1) + \partial \ln(C) / \partial \ln(y_2)$, computed for each bank-year observation from translog coefficients. $EC > 1$ indicates diseconomies of scale. All 525 observations have $EC > 1$.

Corr.	Cost Eff.	NPL Ratio	ROAA	CIR
Cost Efficiency	1.000	-	-	-
NPL Ratio	0.017	1.000	-	-
ROAA	-0.124**	-0.391***	1.000	-
CIR	0.277***	0.103*	-0.503***	1.000

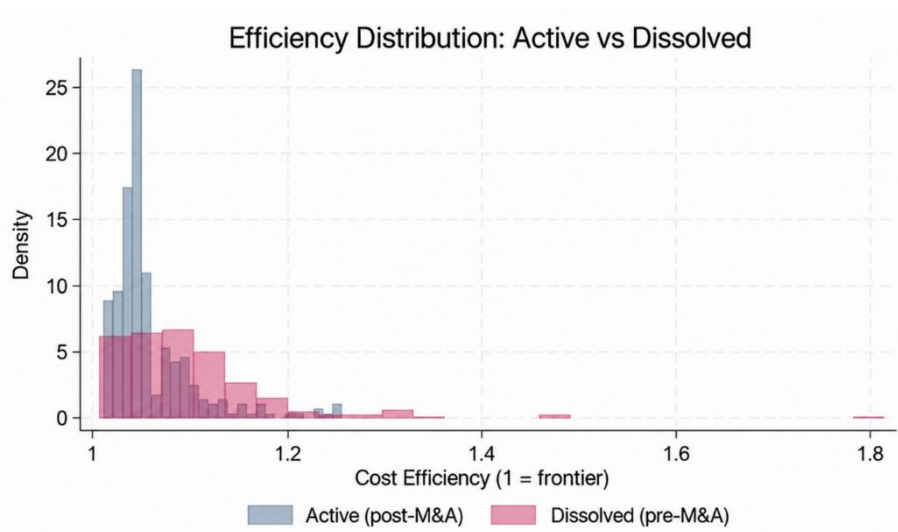
Table 4.5 Pairwise Correlations Among Key Performance Variables Notes: Pairwise Pearson correlations; N = 505 (observations with available NPL data). *, **, *** denote significance at 10%, 5%, and 1% respectively. p-value for the cost efficiency / NPL ratio correlation = 0.71.

Period	N	Active	Dissolved	Gap (pp)	Context
Pre-crisis (05–07)	70	1.072	—	—	Only active observed
Crisis (08–12)	73	1.076	1.091	1.5	GFC + sovereign crisis
Post-crisis (13–15)	242	1.054	1.102	4.8	NPL crisis, early reforms
Reform era (16–20)	113	1.049	1.116	6.7	BCC/Popolari reforms
Post-COVID (21–24)	27	1.093	1.085	–0.8	Limited sample (N=27)

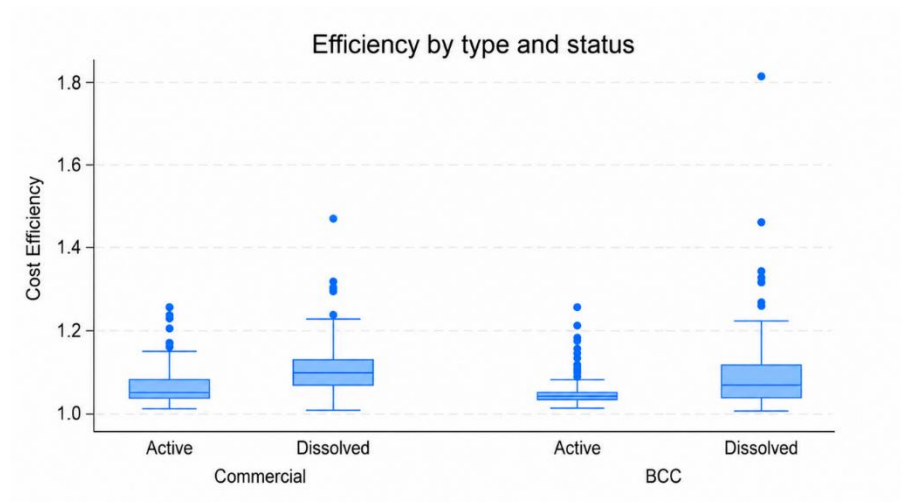
Table 4.6 Cost Efficiency by Historical Period and Bank Status Notes: Pre-crisis period contains only active bank observations. Post-COVID results should be interpreted with caution given the small sample (3 active, 24 dissolved observations).

Variable	-1	-2	-3	-4	-5	-6
Dissolved	0.035***	0.036***	0.036***	0.034***	0.031***	0.035***
BCC	–0.011*	–0.010*	–0.010	–0.010**	–0.010**	–0.010*
Dissolved × BCC		–0.001				
ln(Total Assets)	0.008***	0.008***	0.009***	0.010***	0.010***	0.011***
NPL Ratio			–0.000	0.000	0.000	0.000
Tier 1 Ratio				0.000	0.001	0.000
Equity / TA				0.002	0.002	0.003*
ROAA					–0.005	–0.004
EC (scale elast.)						–0.207
N	525	525	505	497	497	497
R ²	0.134	0.134	0.136	0.171	0.178	0.181

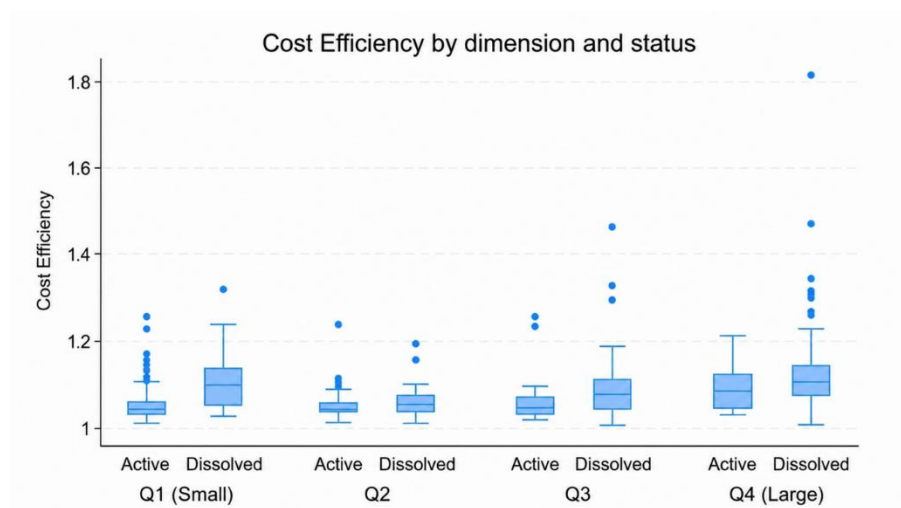
Table 4.7 – Second-Stage Regressions: Determinants of Cost Efficiency Notes: Dependent variable is cost efficiency ($CE \geq 1$). Robust standard errors throughout. *, **, *** denote significance at 10%, 5%, 1%. Model (1): structural variables only. Model (2): adds dissolved×BCC interaction. Model (3): adds NPL ratio. Model (4): adds capitalisation. Model (5): adds profitability. Model (6): adds scale elasticity.



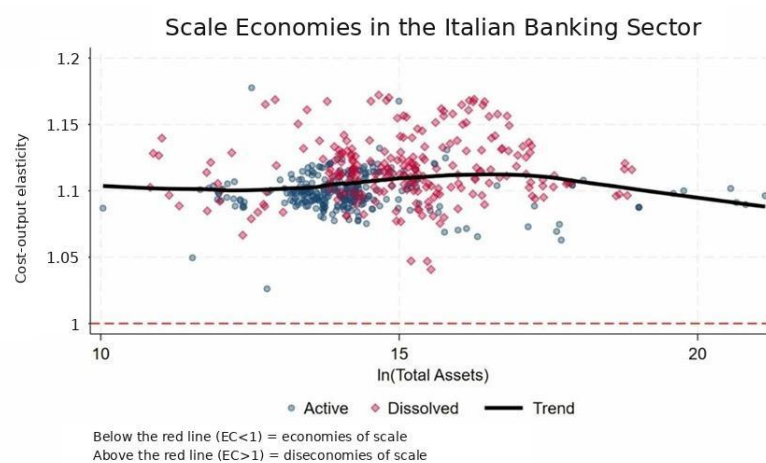
Graph 4.1 Overlapping histogram of cost efficiency scores: active banks versus dissolved banks.



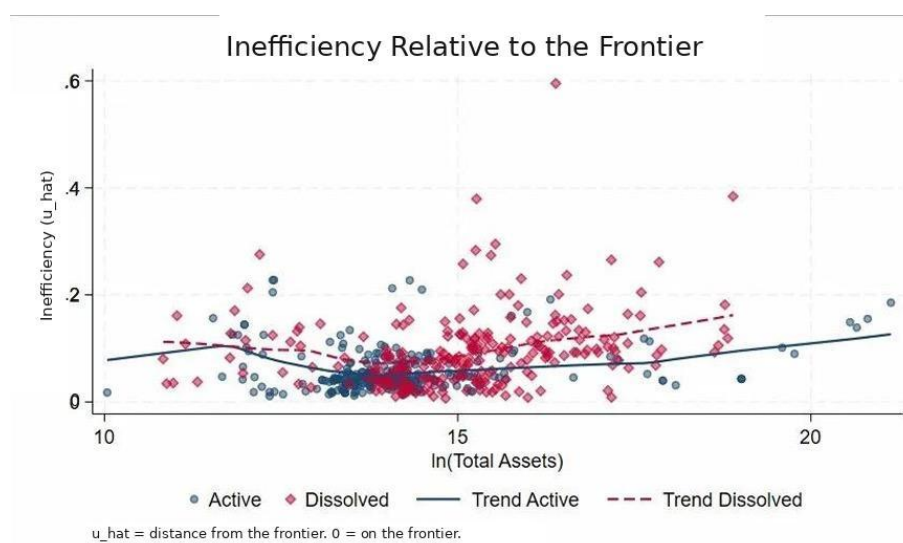
Graph 4.2 Box plot of cost efficiency by size quartile and bank type.



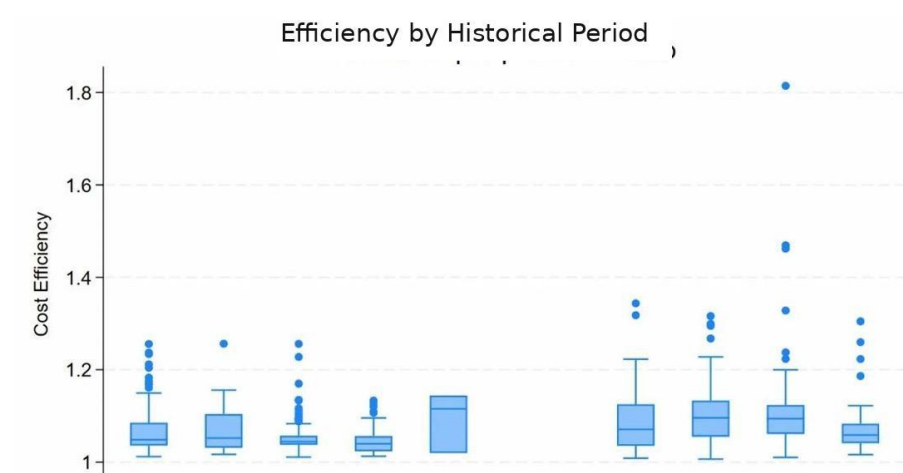
Graph 4.3 Bar chart of mean efficiency by size quartile, active versus dissolved.



Graph 4.4 Scatter plot of cost elasticity (EC) against $\ln(\text{Total Assets})$, active versus dissolved, with trend line



Graph 4.5 Scatter plot of inefficiency (u_{hat}) against NPL ratio, with lowess trend line, active versus dissolved.



Graph 4.6 Box plot of cost efficiency by historical period and bank status. Active banks on the left and dissolved banks on the right. Per each group from left to right the box plots represent: 1 the pre crisis period (2005 to 2007); 2 the financial and sovereign debt crisis (2008 to 2012); 3 the post crisis years (2013 to 2015); 4 the reform era (2016 to 2020); 5 the post COVID period (2021 to 2024).

Chapter 5

Variable	BCC	Commercial	Diff.	t stat	p value
Interest Expense Share	0.290	0.286	-0.004	0.307	0.759
Operating Expense Share	0.710	0.714	+0.004	-0.307	0.759
Loan to Assets Ratio	0.653	0.644	-0.009	0.599	0.549
Securities to Assets Ratio	0.275	0.286	+0.011	-0.744	0.457
Cost to Income Ratio	71.75	74.08	+2.33		

Table 5.1 Cost Structure by Bank Type (BCC vs. Commercial) Source: authors' calculations on Orbis/BankFocus data. Two sample t test with unequal variances.

Variable	Active	Dissolved	Diff.	t stat	p value
Interest Expense Share	0.33	0.24	+0.09	5.82	< 0.001
Operating Expense Share	0.67	0.76	-0.09	-5.82	< 0.001
Loan to Assets Ratio	0.59	0.72	-0.13	-6.41	< 0.001
Securities to Assets Ratio	0.36	0.19	+0.17	7.93	< 0.001
Cost to Income Ratio	0.66	0.81	-0.15	-8.17	< 0.001

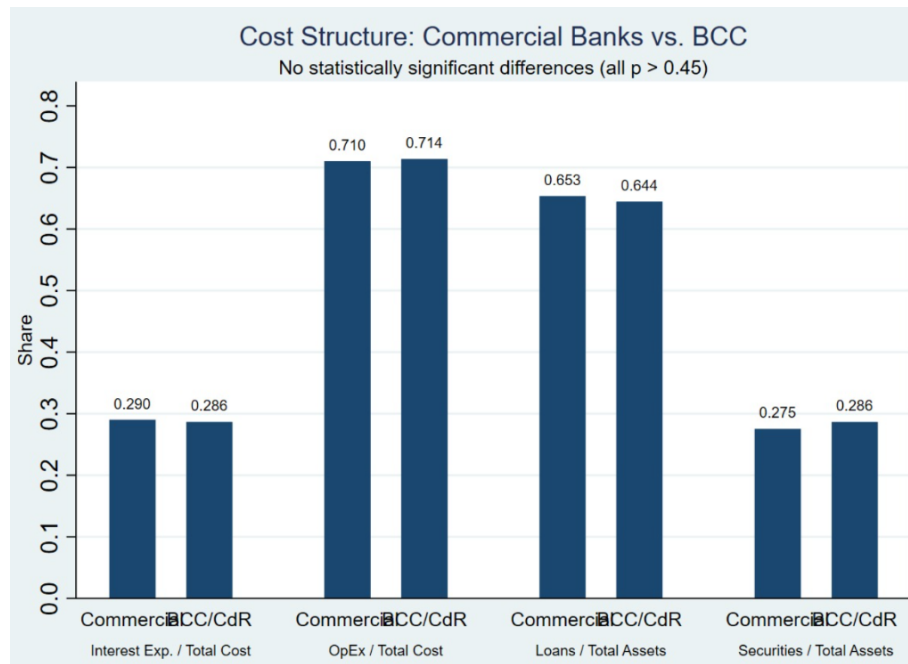
Table 5.2 Cost Structure by Bank Status (Active vs. Dissolved) Source: authors' calculations on Orbis/BankFocus data. Two sample t test with unequal variances. All differences significant at the 0.1% level.

Group	Loan Share	Securities Share	Scope Benefit
Active Banks	0.59	0.36	0.334
Dissolved Banks	0.72	0.19	0.193
Difference	—	—	0.141

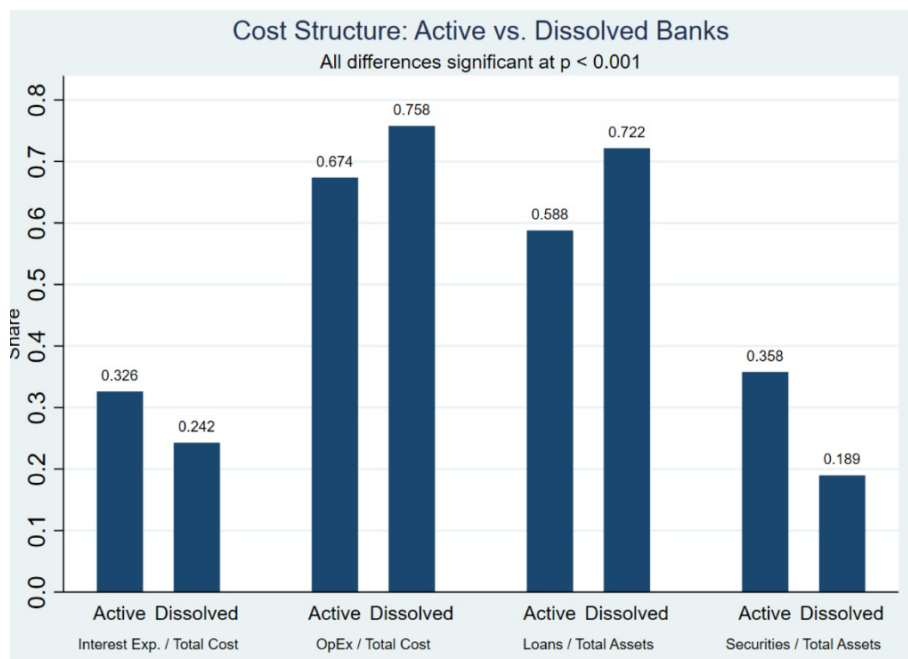
Table 5.3 Economies of Scope by Bank Status Source: authors' calculations. Scope benefit computed as the absolute value of the cross term coefficient (-0.164) multiplied by the product of the log normalised output shares, evaluated at group means.

Metric	Active	Dissolved	Diff.	p value
Cost Structure				
Interest Expense Share	0.33	0.24	0.09	< 0.001
Operating Expense Share	0.67	0.76	-0.09	< 0.001
Asset Composition				
Loan to Assets Ratio	0.59	0.72	-0.13	< 0.001
Securities to Assets Ratio	0.36	0.19	0.17	< 0.001
Efficiency Measures				
Cost Efficiency Score	1.059	1.102	-0.042	< 0.001
Cost to Income Ratio	0.66	0.81	-0.15	< 0.001
Cost Output Elasticity	1.099	1.117	-0.018	< 0.001
Scope Benefit	0.334	0.193	0.141	—

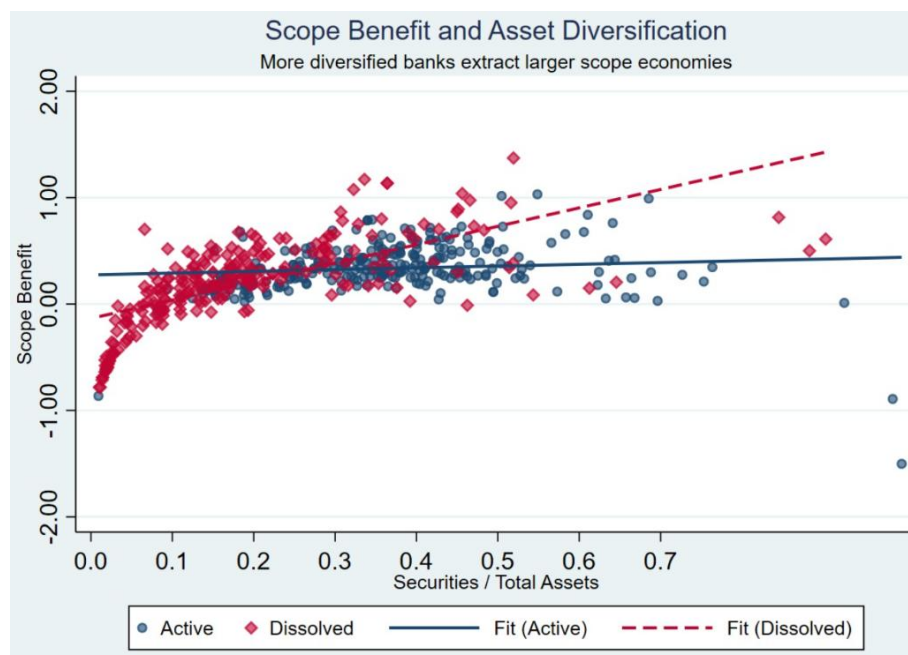
Table 5.4 Summary: Cost Structure and Efficiency by Bank Status Source: authors' calculations on Orbis/BankFocus data.



Graph 5.1 Bar chart of the four cost structure ratios side by side .



Graph 5.2: Asset composition bar chart.



Graph 5.3: Loan to assets ratio and cost efficiency score.

Chapter 6

	Half Normal	Exponential
Log likelihood	731.46	762.89
λ (lambda)	3.752	2.011
LR test of $\sigma_u = 0$	$\chi^2 = 90.94, p < 0.001$	$\chi^2 > 150, p < 0.001$
Mean efficiency (all)	1.079	1.061
Mean efficiency (active)	1.059	1.046
Mean efficiency (dissolved)	1.102	1.080
Dissolved – active gap	4.2 pp	3.5 pp
t test for gap	$t = -7.19, p < 0.001$	$t = -5.57, p < 0.001$
Correlation between scores	$\rho = 0.974, p < 0.001$	

Table 6.1 Comparison of half normal and exponential SFA models

Rank	Bank	Status	Type	Eff.	TA (€m)	CIR (%)
1	Banca di Valle Camonica	Dissolved	BCC/CdR	1.013	2,368	70.0
2	Banca delle Marche	In Liquidation	Comm.	1.015	28,095	59.7
3	Banca Alpi Marittime CC	Active	Comm.	1.017	750	99.1
4	Cassa Raiffeisen Brunico	Active	BCC/CdR	1.017	1,441	79.4
5	BCC San Giovanni Rot.	Active	BCC/CdR	1.017	663	73.9
6	Bca Cred. Peloritano	Active	BCC/CdR	1.019	363	56.3
7	BCC Recanati e Colm.	Active	BCC/CdR	1.020	685	66.7
8	Banco Fiorentino	Active	BCC/CdR	1.021	1,860	61.6
9	Vival Banca BCC	Dissolved	BCC/CdR	1.021	1,257	92.2
10	Banca di Imola	Dissolved	Comm.	1.022	3,500	65.0

Table 6.2 Top 10 most efficient banks (bank level averages)

Rank	Bank	Status	Type	Eff.	TA (€m)	CIR (%)
1	Depobank	Dissolved	BCC/CdR	1.380	12,656	100.1
2	Banco Emiliano Romagn.	Dissolved	Comm.	1.318	198	378.6
3	UBI Banca	Dissolved	Comm.	1.272	149	90.7
4	IW Bank	Dissolved	BCC/CdR	1.259	4,928	81.9
5	Cassa Centr. Raiffeisen	Active	Comm.	1.242	1,640	61.3
6	Bancapulia	Dissolved	BCC/CdR	1.221	3,820	118.4
7	CR di Cesena	Dissolved	BCC/CdR	1.218	4,085	378.8
8	Nuova CR di Ferrara	Dissolved	Comm.	1.208	6,376	109.0
9	Banca Stabiese	Active	Comm.	1.206	229	41.8
10	Bca Pop. di Vicenza	Dissolved	Comm.	1.197	45,341	107.5

Table 6.3 Bottom 10 least efficient banks (bank level averages). * In Billions of euros

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