BANK MERGERS, DIVERSIFICATION AND RISK

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Diversification is the standard approach to managing the trade-off between portfolio risk and return. Banking consolidation, increasing risk diversification, should in principle result in banking firms that are better diversified and hence less likely to fail. In turn, this should create a healthier banking system that is less prone to banking crises.
However, the G-10 "Report on Consolidation in the Financial Sector", (2001) finds that (a) the effects of financial consolidation on the risk of individual banks are mixed, the net results impossible to generalize and a case-by-case assessment is required.; (b) *after* (emphasis added) consolidation, banks may become riskier because they chose to take on more risk or because loan monitoring is reduced or less effective.
While we agree that the effect of consolidation on individual bank risk depends on the characteristics of each merger, i.e. on the combination of the risk profiles of the acquiring and the target bank, we emphasize that the actual results are highly dependent on the way risk is modeled.
In this paper we restrict our attention to *credit* risk and we measure it using the same methodology - a portfolio credit risk model - employed by the major banks to quantify their economic risk.
Using data on *individual* firm exposures and probabilities of default and bank-level data on loss given default, we compare the pre- and post- merger credit expected and unexpected loss for a sample of M&As in the period 1997-2001. We find that, as a consequence of a merger, credit risk is significantly reduced because of diversification of idiosyncratic risk.
To test the hypothesis of riskier policies caused by the mergers, we also analyze the same statistics two years after the deal and find no significant changes in banks' portfolio risk and insolvency probability. On the contrary, the evidence shows an increase in lending to more creditworthy borrowers and a larger diversification of systematic risk.

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1. Introduction

Over the last fifteen years the banking and financial systems of the industrialised countries have been undergoing rapid changes prompted by deregulation, innovations in information technology, and the globalisation of markets.

The pressure of competition pushed banks into searching for ways to widen their geographical reach and range of products, with a view to achieving economies of scale and scope and improving their efficiency.

According to Thomson Financial, in the 1996-2001 period there were 3,200 mergers and acquisitions in which a bank was involved as a target in the Group of Ten countries, Spain and Australia. The total value of such operations jumped to $ 1,3 trillion, from $ 295 billion in the 1990-95 period.

Such a sharp increase in M&A activity deserved an impressive body of theoretical and empirical research addressing the key aspects of financial consolidation.

In this paper we will concentrate on the effects of the consolidation process on financial risk. The G-10 report issued in 2001, when arguing that financial consolidation can affect the risk both of individual intermediaries and of a systemic financial crisis, will provide the basic framework of our empirical work.

The reference to Italy is justified by the high number and value of the deals: since 1990 higher overall values have been recorded only in Japan and in the US. Moreover, by referring to Italy we will be able to exploit a very detailed body of information, ranging from regulatory reports, the Credit Register and the balance-sheets of commercial and industrial firms.

The results of previous empirical studies are rather mixed. In principle, banking firms should become less prone to a crisis as a result of consolidation, in connection with a better diversification of their assets. However, after consolidation the banks might choose to take on more risk according to a *too-big-to-fail* behaviour or because loan monitoring is reduced or less effective.

Furthermore, diversification achieved through expansion into newer or competitive industries may lead to a deterioration in the quality of assets due to a lack of knowledge about new markets and increased adverse selection in the pool of bank borrowers.

In order to examine the combination of the risk profiles of the acquiring and the target banks, we use a *value-at-risk* model that has been developed with specific reference to the Italian framework.

In such models risk is measured as the uncertainty of future credit losses around their expected mean. Economic capital, that is the amount of equity necessary to cover unexpected losses, may be taken as a synthetic indicator of the overall riskiness of a bank asset portfolio.

In this paper we focus on the risk arising from bank loan portfolios, using data on individual firm exposures, probabilities of default of 180,000 non financial companies estimated on the basis of balance-sheet and Credit Register data, and a measure of *loss given default* drawn from a survey conducted among Italian banks[2].

Unexpected losses are determined taking into account the concentration of exposure: (a) to individual borrowers (diversification of idiosyncratic risk); (b) to specific types of industries and/or geographic regions, that are highly susceptible to correlated defaults due to systematic risk.

For all M&As among Italian banks in the period 1997-2001, excluding those for which the target banks were not large enough to affect the risk profile of the acquiring bank, we measure pre- and post- acquisition economic capital of the acquiring bank, in order to assess the impact of consolidation over firm risk.

The paper also provides a detailed analysis of how the composition of bank credit portfolios has been changed in a time span after the consolidation, in order to assess whether merged banks do actually shift the composition of their credit portfolios towards less creditworthy borrowers and the effect of post-merger credit policies on portfolio's risk.

2. Theoretical background and previous evidence

The impact of M&As on financial stability can be split into two different effects:

(i) the effect on credit risk of the individual institutions involved in the deal;

(ii) the systemic consequences of relying on a higher number of larger institutions, which in turn should be evaluated under two main viewpoints:

- larger banks could be more prone to *moral hazard* and too-big to discipline effectively, supervise and wind down;
- the failure of a larger bank would put substantial strain on the financial system, because it can directly impose losses on other institutions and can also create doubts about the health of other institutions (Mishkin, 1999).

[2] In addition to credit risk, the consolidation process affects all types of risk facing the banks (market risk, liquidity risk, operational risk), especially when it leads to the formation of financial conglomerates. However, while recent methodological advances have been made in measuring individual risk types, a number of conceptual and practical difficulties still need to be solved when models seek to aggregate risks across areas, markets and business lines on a firm-wide basis. For a discussion on this topics see Bikker and van Lelyveld (2002) and Federal Reserve Bank of New York (2000).

Different opinions have been presented regarding the expected consequences of the deals on the insolvency risk of individual banks and a mixed empirical evidence has been developed using as an indicator of risk bank returns' volatility, a particular measure of a bank's probability of default[3], known as Z-score, or market valuation.

Researchers following the traditional portfolio theory focused their attention on the diversification benefits of the mergers: a larger coverage of geographic areas and sectors, under the condition of imperfectly correlated risks, tends to improve bank safety.

Benston, Hunter and Wall (1995) show a negative relationship between the purchase premium and the target's expected contribution to the risk of the new organization, proxied by the variance of the target's return on assets and the covariance between the acquirer's and the target's ROA, both computed prior to the acquisition.

Proxying risk both by the variability of profit indicators and a Z-score, Craig and Cabral dos Santos (1997) compare: (a) the post-acquisition risk of the newly formed organization and the pre-acquisition risk of the acquiring BHC; (b) the post-acquisition risk of the acquired bank and the pre-acquisition risk of the same bank; (c) the pre and post-acquisition risk of the hypothetical banking organization that would result from the aggregation of the acquiring bank and of the acquired bank. Their empirical results suggest that consolidation is producing less risky organizations, since acquisitions turn out to have a positive impact on the profitability of participating institutions, particularly acquired banks.

According to Hughes, Lang, Mester, and Moon (1999), the banks' probability of remaining solvent tends to increase in connection with consolidation strategies enhancing geographic diversification. However, their empirical results seem to show that it takes a few years for the full benefits of diversification to develop after acquisitions, or that there are rapidly diminishing returns to geographical diversification. This interpretation seems consistent with Cerasi and Daltung (2000) stressing that the marginal cost of monitoring is increasing, due to individual banker's limited resources and organizational complexities.

A series of theoretical arguments have been made in order to show that consolidation and increased diversification of assets do not necessarily turn out to be beneficial to the stability of individual institutions.

Shaffer (1989) argues that, differently from what the usual concept of diversification of risk would suggest, the sharing of resources among a group of organizations increases the probability of failure for the entire group relative to the situation in which the organizations operate independently. The economic rationale has to do with the involvement of all the entities

[3] This measure, known as Z-score, is a measure, expressed in units of standard deviation of ROA, of how much a

included in the pool in the case in which one of them becomes distressed. When the firms are operated separately, either firm is dropped from the market if its net worth falls below a given threshold. On the contrary, in the pool any outcome for one firm that occurs below the threshold becomes a corresponding burden on the other firms, or on the pool as a whole.

Winton (1999) and Gorton and Winton (2002) emphasize that the quality of credit portfolios is *endogenous*, because the bank chooses the level of monitoring of its loans. This choice can be affected by the extent of debt in the bank's capital structure and by the diversification of assets. The impact of diversification changes according to whether the bank's ability to monitor loans is different across different sectors and to the loans' exposure to sector downturns: (i) if the bank lacks a sufficient knowledge of the markets in which it is going to enter, diversification can translate into increased monitoring difficulties; (ii) if the home sector has a low downside risk, diversification can actually increase the bank's insolvency risk. Moreover, an increase in the probability of default reduces the incentives of bank-owners to bear the costs of monitoring. In fact, if the loan portfolio has high downside risk, then an improvement in loan monitoring and, in turn, in loan quality produces greater benefits to the creditors than to the bank-owners.

De Nicolò (2000) provides empirical evidence on the cross-sectional relationships between bank size and market measures of charter value and insolvency risk with reference to a sample of publicly traded banks in 21 industrialized countries for the 1988-98 period. Insolvency risk, proxied by a Z-score, turns out to increase with size, meaning that size-related diversification benefits and /or economies of scale in bank intermediation are either absent or, if they exist, are more than offset by banks' policies or increased complexities. As a consequence, bank consolidation is likely to have a detrimental effects on the safety of individual institutions.

Acharya, Hasan, and Saunders (2002) provide some empirical evidence regarding Italian banks confirming Winton's intuition. The asset diversification, as measured by an Herfindahl index of six industrial sector exposures, turns out to help a bank's return only slightly when loans have moderate downside risk; when loans have a sufficiently high downside risk, diversification may actually reduce returns. Moreover they find evidence that when banks enter as lenders into "newer" industries, there is a contemporaneous deterioration in their loan quality, proxied by the ratio between doubtful and non-performing loans and total assets, the standard deviation of this ratio and the ratio of loan-loss provisions to assets. On the basis of these results the authors argue that there may exist diseconomies of diversification due to poor monitoring incentives or to an adverse selection problem in new sectors of activity.

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bank's accounting earnings can decline before the bank exhausts its equity capital and becomes insolvent.

However, Acharya, Hasan, and Saunders (2002) seems to suffer from a series of shortcomings, mainly connected with the definition of credit risk and with the treatment of Italian data. Using the ratio between doubtful and non-performing loans and total assets as a proxy of expected losses (and its standard deviation as a proxy of unexpected losses) seems disputable, given that the level of the ratio basically reflects the quality of lending decisions that have been taken in the past. In fact, the only possible measure of expected losses can be drawn from the probabilities of default of bank borrowers and the *loss given default* of lending operations. Furthermore, their measure of diversification is based on a too limited number of sectors and no reference is made to geographical diversification of assets, so that the results can hardly be taken as conclusive. Finally, they did not consider that their sample period was characterized by a large number of M&A deals, so that almost all banks had significant changes in the balance sheets and in the ownership links which should be taken into account properly.

In fact, the knowledge and the understanding of the markets in which the acquiring bank is going to enter cannot be taken for granted. In principle, entry could determine an increase in the bank's insolvency risk, mainly due to a "winners curse" effect. However, this is not the case if the entry into unfamiliar sectors is made by merging with already established institutions or by taking the control of their voting rights, because this implies acquiring their information and lending expertise (Gorton and Winton, 2002).

As regards financial risk at a systemic level, the attention has been focused on the portfolio choices of the merged banks, which could decide to pursue risky strategies: this would raise the probability that the institution will fail before settling some of its payment obligations vis a vis other intermediaries. As a consequence one bank's failure could propagate to the rest of the system. Moreover the crisis of a larger bank is more likely to spread panic among depositors and investors.

Berger (1998), Boyd and Graham (1998), Berger, Demsetz, and Strahan (1999), De Nicolò (2000), Gorton and Winton (2002), Hughes, Lang, Mester, and Moon, C. (1999), and Hughes, Mester, and Moon (2001), among others, argue that larger banks are more exposed to *moral hazard*, as a result of being *too-big-to-fail*. As a consequence larger banks could misuse the diversification gains to engage into risky strategies without the market requiring additional capital or higher interest rates on uninsured debt. On the basis of such arguments, some proposals have been made in order to reduce the deposit insurance protection to large banks, or to introduce some constructive ambiguity into the safety net, or to make bank supervision more stringent on systemically relevant institutions (Mishkin, 1998 and Mishkin, 1999).

Different opinions have also been expressed with reference to another aspect of relationship between M&As and systemic stability, that is the problems connected with the coexistence of institutions of a different size and portfolio diversification.

According to Paroush (1995), it is not possible to apply to the banking system the same conventional wisdom usually applied to other industrial sectors, according to which increasing welfare is normally associated with a large (or rising) number of competitors and competition among the many is considered superior to competition among the few. In the banking industry there is a cost connected with the number of institutions in the system: every bank has a positive probability of failure and, since a bank failure puts substantial strain on the system, the system becomes more fragile as the number of banks increases**.** In the recent years, the system has reacted through increased frequency of failures and M&A to factors driving the optimal number of banks downwards, such as increasing competition, accelerated development of capital markets, high volatility of interest rates and exchange rates, increased sophistication of new financial products. According to this line of argument "any act of business combination reduces in general the total amount of risk and therefore most likely increases the safety and soundness of the banking system". This reduction is connected both with the direct effect of reducing the total risk of the system because of the decrease in the number of banks and with a lower probability of failure of the merged banks.

Some authors have emphasized the effect of firm inter-dependencies on systemic risk: even if more diversified banks would turn out to be more stable, this should not be considered as a sufficient condition for reduced systemic risk.

As pointed out by De Nicolò and Kwast (2002) firm inter-dependencies may be both of a direct and indirect nature: direct inter-dependencies arise from interbank lending and counterparty exposure on derivatives and repurchase agreements; indirect inter-dependencies stem from exposures to the similar counterparties. They find that firm inter-dependencies, as measured by the correlations of stock return, has been increasing over 1990s among a sample of systemically relevant US banks. However, they also find that the contribution of consolidation to the upward trend in return correlation has been declining in the latter part of the 1990s, the period in which the consolidation process gathered momentum, so that other factors should be carefully studied.

Both Acharya (2001) and Tsatsaronis (2002) focus on the correlation of balance sheets across individual institutions, consistently with a definition of systemic risk focused on the exposition of banks to the common macroeconomic factors, rather than on domino effects. Commonalties in risks may be increased if financial institutions follow similar patterns of exposures to a number of diversifiable risk factors, as it might be the case of a consolidation process leading to a small number of banks operating in the same regions and sectors or in a framework in which banks deliberately choose to lend to similar industries in order to exploit the implicit guarantee of a *too-many-to-fail* situation.

An extremely comprehensive overview of the whole topic of consolidation and financial risk has been provided by the report issued in 2001 by the Group of Ten, whose main conclusion can be summarised by the following sentence: "In part because the net impact of consolidation on individual firm risk is unclear, the net impact of consolidation on systemic risk is also uncertain". This is basically the result of two analytical and empirical points stemming from the body of literature that has been surveyed: (1) "The one area where consolidation seems most likely to reduce firm risk is the potential for diversification gains"; (2) ".. after consolidation some firms shift toward riskier asset portfolios".

Giving an empirical content to such arguments may contribute to make the potential effect of consolidation on financial risk more clear-cut.

We will follow the argument made in the G-10 report according to which "The potential effects of financial consolidation on the risk of individual financial institutions are mixed, and the net result impossible to generalise. Indeed the analysis strongly indicates that, when it comes to evaluating individual firm risk, a case by case assessment is required".

Therefore, our empirical research will adopt a case by case approach in referring to the M&A activity recently performed in the Italian banking system.

3. Bank consolidation in Italy

The empirical analysis will be referred to the Italian banking system, whose structural features have undergone a dramatic change in the short space of ten years.

At the end of the eighties the Italian banking system was highly fragmented, with a large number of small and medium-sized banks engaging mainly in deposit-taking and lending in local markets. The legal barriers between different categories of banks and the administrative constraints on the opening of new branches were an obstacle to the enlargement of the banks operating throughout the country. The bulk of banking business was carried out by public sector banks, where the granting of credit overlapped with objectives of a public nature; the legal form of such banks and their limited ability to raise capital were an obstacle to mergers permitting the rationalisation of corporate structures.

As in other industrial countries, since that time far-reaching regulatory changes have been introduced, in response to the integration of financial markets and advances in information technology. Entry controls have been removed; the supervision of individual banks has been based on criteria designed to ensure capital adequacy and respect banks' autonomy in the allocation of financial resources; the 1993 Banking Law sanctioned the principle of competitive equality among all banks by eliminating operational specialisation. Legislative reform aimed at facilitating the privatisation of public sector banks was initiated in 1990.

The privatisation of banks and their listings on the stock exchange have made their ownership and control fully contestable.

Under the pressure of increasing competition, Italian banks have carried out a large number of M&A operations aimed at achieving economies of scale and scope and entering new fields of activity. In terms of the prices paid, the consolidations carried out in Italy between 1990 and 2001 had a value of $ 100 billion, lower than in the US, UK and Japan, but higher than in the other main industrialised countries (Table 1).

TABLE 1: Mergers and Acquisitions in the main industrial countries (1)

Countries	1990 - 1995		1996 - 2001	
	Number of deals	**Total value $ billion**	**Number of deals**	**Total value $ billion**
Main Industrial Countries (2)	**2,631**	**295.1**	**3,183**	**1,316.6**
of which **US**	**1,691**	**156.6**	**1,796**	**754.9**
Japan	**29**	**44.4**	**236**	**119.1**
UK	**140**	**33.0**	**279**	**114.4**
Euro Area	**655**	**59.6**	**700**	**302.8**
of which **Italy**	**147**	**19.2**	**138**	**80.4**

(1) Mergers and acquisitions with a bank as a target involving majority interests.
(2) G10 countries, Australia, Spain

Between 1990 and 2002 there were 580 concentrations in Italy (without taking into account intra-group operations) involving target banks holding 50 per cent of the banking system's total assets at the beginning of the period (Table 2). The number of banks declined from 1,176 to 814. In connection with the consolidation process, the market share of banks more than half-owned by public entities fell from two thirds to 10 per cent.

In 176 deals, involving banks with assets equal to 36 per cent of the industry total, the institutions taken over maintained their own corporate identities. The acquiring banks preferred to keep the target banks as separate in order to combine the advantages of brand preservation with those deriving from the coordinated monitoring of risks, the curbing of costs and the integration of policies for the production and marketing of services. In particular they aimed at fully exploiting the target banks' knowledge about the system of small and medium-sized enterprises.

TABLE 2: MERGERS AND ACQUSITIONS IN THE ITALIAN BANKING SYSTEM

Years	Merges and incorporations		Acquisitions	
	Number of deals	Total assets (%)	Number of deals	Total assets (%)
1990	19	1.07	4	0.37
1991	33	0.45	5	0.37
1992	20	3.04	1	0.01
1993	38	0.63	6	1.50
1994	42	1.59	10	1.90
1995	47	1.54	19	4.50
1996	37	0.47	19	1.08
1997	24	0.80	18	3.42
1998	27	2.65	23	11.02
1999	36	0.39	28	14.21
2000	33	1.50	24	4.86
2001	31	0.08	9	1.55
2002	17	0.05	10	4.94
Total	**404**	**13.74**	**176**	**36.14**

The whole system has been recast mainly in the form of banking groups, to which now belong more than four fifths of all branches. The concentration of the banking system, measured on the basis of the market share of the five largest groups, has reached 55 per cent, in line with the figure for France and Spain, higher than that for Germany and the United States.

4. Measuring credit risk

The most widely accepted approach to risk in financial markets focuses on the measurement of volatility in return distributions[4]. This form of risk quantification finds its origins in the seminal work of Markovitz (1952) and (1959), who finds that each portfolio construction decision can be structured in function of the expected mean and standard deviation (volatility) of the portfolio return. Unless the returns on the assets in the portfolio are perfectly positively correlated, the risk of a diversified portfolio will be less than the weighted average of

[4] This section draws on Alexander (1999), that surveys standard approaches to measuring and modeling financial risks and portfolio risk models, Ong (1999), Saunders (1999), Jones and Mingo (1999), Crouhy, Galai and Mark (2000) for surveys on credit risk models.

the risk of the individual assets. The portfolio risk will be lower the lower the correlations between the constituent asset returns.

Implementing this approach to measuring risk requires the knowledge of the "full covariance matrix", e.g. an exact measure of means, standard deviations and correlations of all assets included in the portfolio. Due to severe implementation problems, academic research in finance had concentrated in modeling the risk in function of the underlying asset characteristics. It is now generally recognized that risk is multidimensional, i.e. the volatility of portfolio returns depend on the variances and covariances between the risk factors of the portfolio, and the sensitivities of individual assets to these risk factors (multiple factor models).

This approach to modeling risk is at the basis of all risk measurement and management activities. The way in which it is implemented is highly dependent on the objective and the time frame. Typically, traders, corporate treasures and market makers worry about how much money they might gain or lose, given their current positions: for this reason they tend to rely on the measurement of *value at risk* (VaR), that is generically defined as the maximum possible loss for a given position or a portfolio within a known confidence interval over a specific time horizon. For trading portfolios, VaR is normally calculated as a multiple of the volatility or standard deviation of the portfolio's returns[5]. The multiple depends on the chosen one-tail confidence interval.

Significant advances have been recently made in applying VaR methodologies to credit portfolios, by taking into account some important differences with respect to trading portfolios.

First, loan returns are asymmetric, with almost no potential for upside gain on loans and substantial downside loss due to a deterioration in the credit quality of the borrowers. As a consequence, the risk associated with a bank credit portfolio is measured by the volatility of losses instead of the volatility of returns.

Second, in principle the default of the borrowers is a rare event; however, when it occurs, the loss is usually substantial. This implies that the portfolio loss distribution cannot be assumed to be normal, as in the case of trading portfolios. On the contrary, it exhibits a high positive skew and fatter tails: in comparison with a normal distribution, there is a larger probability of small losses, a smaller probability of large losses and a higher probabilities of very large losses. The percentile levels of the distribution cannot be estimated on the basis of the

[5] The so-called variance/covariance methodology for trading portfolios assumes that position return are jointly normally distributed; the standard deviation is calculated using a set of portfolio position weights and the covariance matrix of position returns.

mean and the variance only, as in symmetric distribution; the calculation of VaR for credit risk requires simulating the full loss distribution.

Third, most standard market risk calculation assume that expected losses (or gains) are equal to zero; given the nature of credit risk, where some losses are likely for all but the most secure, sovereign positions, expected losses are a necessary component of the calculation of VaR.

Fourth, measuring the portfolio effect due to credit diversification is much more complex than for market risk.

Given these differences, the credit risk of a given loan portfolio is defined as the potential for losses due to credit events, i.e. counterparty defaults and rating migrations. The purpose of credit risk models is to estimate the shape of credit loss distributions, i.e. the probability density function of credit losses. "A risky portfolio, loosely speaking, is one with a PDF which has a relatively long, fat tail - that is, where there is a relatively high likelihood that losses will be substantially higher than mean, or expected, losses", (Jones and Mingo, 1999).

In particular, expected losses, as measured by the mean of the distribution, represents the amount the bank can expect to lose, on average, over the chosen time horizon; therefore, it forms the basis for provisioning decisions. The maximum loss within a known confidence interval is used to determine the VaR, defined as the economic capital to be held above and beyond the level of credit reserves, in order to cover unexpected credit losses[6]. To obtain a portfolio's PDF and a measure of unexpected loss it is necessary to determine the joint distribution of defaults across all the counterparties contained in the portfolio. To reduce the dimensionality of this estimation problems, many models use a multi-factor analysis[7].

Multi-factor models assume that the firm's asset returns are generated by a set of common, or systematic, and idiosyncratic factors.

Default correlations arise from a dependence on common or systematic factors. There is evidence that common movements in credit qualities of different obligors are determined to a large extent by macroeconomic, industrial and geographical factors, i.e. in multi-factor models,

[6] The economic capital or credit VaR is determined so that the probability of unexpected losses exhausting economic capital is less than some target level, chosen within prudent solvency guidelines to support the banking activity in most, but not all, cases. The target insolvency rate usually is chosen to be consistent with the bank's desired rating for its liabilities (Jones and Mingo, 2000).

[7] An estimate of a portfolio's PDF can be obtained via Monte Carlo simulations or by using the mean/variance methodology on the basis of an appropriate loss distribution. The mean/variance approach is premised on the assumption that a portfolio's PDF can be reasonably approximated by the probability density function of a beta (or in some cases, normal) distribution. Economic capital is calculated using some multiple of the estimated standard deviation of portfolio credit losses. In the case in which PDF is estimated directly via Monte Carlo simulations, the economic capital allocation is computed directly from the estimated PDF (Jones and Mingo, 2000)

credit losses are correlated to the extent that they are exposed to the same industries and countries.

Default correlation between all obligors in a portfolio is therefore more easily calculated by broadly classifying assets under industry/geographic groups and measuring the correlation between different segments.

The idiosyncratic factors are either firm-, or region- or industry-specific and do not contribute to correlations since they are not correlated with each other and not correlated with the common factors. Only the risk associated with the idiosyncratic risk factor can be diversified away, while the risk contribution of the common factors is, on the contrary, non diversifiable. However, since firms belonging to different segments are influenced by different factors, correlations are expected to be higher for firms within the same industry or in the same region, than for firms in unrelated sector. To the extent that default correlation between segments are low, diversification along the industry and the region dimension helps to reduce the loss volatility[8].

Some multi-factor credit risk models estimate segment-specific default correlations through asset value correlations, calculated using equity and debt price information. In other models segment-specific average default rates, as well as their volatilities, are linked to the macro-economic cycle. Correlations between segments are captured assuming that average default rates by segment are driven by common, macro-economic variables.

5. Methodological issues

In order to study the effects of consolidation on banks' loan portfolio financial risk we use data on individual firm exposures and probabilities of default, and a measure of *loss given default* drawn from a survey conducted among Italian banks. Therefore it was necessary to define:

1. a set of M&A deals in which the target banks' loan portfolios were large enough to affect the risk profile of the acquiring banks;
2. a sample of corporate borrowers large enough to be representative of total C&I loans;
3. a methodology for estimating the individual risk components of a credit risk model, which affect the expected losses: probabilities of default, exposure at risk; loss given default.
4. a credit risk model for assessing the value at risk of each credit portfolio.

5.1 The sample of M&A deals

We studied all mergers and acquisitions performed in the Italian banking market between 1997 and 2001 in which the target bank was large enough to affect the risk profile of the acquiring bank and excluding mergers between mutual banks. This amounted to consider 33 deals where the target bank's exposure was 10 per cent or more of the acquiring one. In our sample three deals involved the acquisition of two target banks

In the same period 253 deals changed the ownership of banks accounting for 40 per cent of total assets at the end of 1996; the target banks included in our sample covered 29 per cent of industry's total assets.

As mentioned above, the Italian consolidation process involved the formation of large banking groups and this is also apparent in our sample. In all cases but four the acquiring institution was a banking group; in ten deals the target institution was also a banking group while in the remaining deals the target institution was an individual bank. Among the target banks or banking groups, 27 maintained their own corporate identities; in a number of cases, the acquired banks were incorporated by the holding banks or other banks of the acquiring group later on. In the paper we use for simplicity the term 'bank' but the characteristics of each deal are properly accounted for in the evidence presented.

On average, the target bank's loan exposure towards non financial firms included in our sample (see below) turns out to be 44 per cent of that of the acquiring institution; the gap is even larger as regards the average number of borrowers (Table 3).

[8] Other approaches assume that default correlations are equal to a constant across all counterparty segments (single-factor models), so that there would be no diversification benefits recognized across multiple customer segments or regions.

TABLE 3: CHARACTERISTICS OF THE BANKS INVOLVED IN THE SAMPLE OF M&As

	Scored borrowers (*)				
	Acquiring bank borrowers / target bank borrowers	Target bank exposure as a share of acquiring bank exposure	Exposure to scored borrowers as a share of total exposure to C&I companies (%)		
			Acquiring bank	Target bank	Merged bank
Mean	6.7	43.8	66.0	66.5	66.5
Median	3.8	33.3	65.8	64.5	66.3
Std	13.4	34.5	8.7	11.8	8.3

(*) borrowers recorded in the Cerved and in the Credit Register to which a PD has been assigned; exposure is EAD

5.2 The sample of non financial firms: the loan portfolios

We considered a set of Italian firms for which individual information on both the financial situation and credit relationships are available.

In fact, quantitative information can be drawn from the CERVED's Company Accounts Register and from the Credit Register run by the Bank of Italy. The Company Accounts Register provides the most comprehensive data on Italian companies, collected since 1993 according to a simplified reclassification scheme of both the balance sheets and the profit and loss accounts including 70 elementary items. The Credit Register records individual credit positions above approximately 75,000 euros; non performing loans are recorded no matter their amount. Its services are available to banks since mid 60s.

It has been possible to define a sample including approximately 180,000 commercial and industrial firms recorded in both registers. Mirroring the composition of the Italian economy, the sample includes a large share of small and medium-sized companies: about 80 per cent of the firms, with sales of less than 5 million euros, account for only 26 per cent of total loans; 1.6 per cent of the firms, with sales larger than 50 million euros, represent 38 per cent of the loans.

The sample turns out to provide a good proxy of the whole credit portfolios, since both for the acquiring and the target banks the exposures towards the borrowers included in our sample represent on average two thirds of total lending to the corporate sector (Table 3).

5.3 Estimating the individual risk components of a credit risk model

We will assume for simplicity that credit losses can arise only if an obligor defaults during the planning horizon, while many models adopt a broader definition of credit events including a downgrading in the creditworthiness of the borrower.

The probability of default is normally determined by consistently classifying each individual counterparty into a specific rating category to which a unique probability of default is associated or by assigning a probability of default to each individual borrower, using statistical scoring methods or option theory[9].

Individual PDs of Italian corporate borrowers can be estimated thanks to a scoring model developed for research purposes at the Bank of Italy on the basis of quantitative information drawn both from the CERVED's Company Accounts Register and the Credit Register (Cannata, Fabi and Laviola, 2002).

In particular, balance sheet data at time t and Credit Register information at time $t+1$ are used to assess the probability of each firm of being recorded as defaulted at time $t+2$. A firm was regarded as defaulted if it was reported in the Credit Register's bad debt category for the first time in the year $t+2$ by at least one lending bank[10].

The target of the analysis is to estimate the best-fitted weighted combination of risk-meaningful variables in order to distinguish sound from insolvent firms. The estimated *logit* function is then used out of the sample to forecast a risk score for companies for which such variables are available.

The 180,000 firms included in our sample have been split into four sectors of economic activity (manufacturing, trade, construction, and services) in order to estimate a separate regression model for each sector. For every model, two thirds of the firms were used to fit the data; the rest were used to test out of sample. Since in the estimation sample the proportion of sound and insolvent firms mimics that of the universe, the forecast values of the logistic regression can be regarded as the probability of default of the individual firms within one year.

Through a stepwise procedure, 11 significant explanatory variables were selected out of about 30 ratios proxying for profitability, productivity, liquidity, financial structure, tension in credit relationships, growth, size and geographical location of the enterprises (Table 4).

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[9] Foglia, Iannotti, and Marullo Reedtz, (2001) discuss how to calibrate a statistical scoring model.

[10] In the Credit Register bad debts are defined as all exposures to insolvent borrowers, regardless of any collateral received. Debtors are considered insolvent if they are globally unable to cover their financial obligations and are not expected to recover, even if it does not necessarily result in legally ascertained bankruptcy. It is important to note that this definition of default is narrower than the one endorsed by the Basel Committee in the New Capital Accord, which also covers substandard loans and loans 90 days past due; the resulting scores therefore overestimate the credit quality of borrowers. Moreover, the default rate in our sample turns out to be lower than the default rate of all

TABLE 4: Estimating the probability of default - Logistic regression

Significant explanatory variables

	ECONOMIC SECTORS			
	INDUSTRY	**COMMERCE**	**CONSTRUC.**	**SERVICES**
- "geographical" (dummy) variables				
Central Italy	**	*	**	
Southern Italy	***	***		
- "Credit Register" variables				
Amount drawn / granted (yr.avg.)	***	***		***
Overshoot (avg.num.)	***	***	***	***
Δ (Amount drawn / granted)	***	*		
- "Balance-sheet Register" variables				
Value added / Total Assets		**		
Current Assets / Current Liabil.	***			
Cash Flow / Total Assets	***			***
Coverage Ratio	**	**	**	
Leverage Ratio	***	***	***	***
Long Term Debt / Total Debt				***

(1) Significance levels (Wald chi-squared statistic) *** : 0,1% ** : 1% * : 5%

The overall correct classification rate - the fraction of firms that are correctly classified by the model as sound or insolvent - is around 74 per cent on average (Table 5). For each sector, the values of the cut-off points have been chosen so that "Type I" and "Type II" errors are equal. Out of sample, similar percentages are observed for both sound and insolvent firms. Adding the Credit Register variables to the regression considerably improved the classification rate of the models. compared with one using only balance-sheet data[11].

bank corporate borrowers recorded in the Credit Register, an indication that credit quality of firms recorded in the CERVED Register is biased upwards.

[11] The overall performance has also been assessed using the power curve (or 'Gini curve'), considering the results of the model out of the sample in the year of estimation and on the full sample in other periods. This curve measures the discriminatory power of the function, that is, the overall ability of the model to distinguish sound from insolvent firms. A related measure is the accuracy ratio, the ratio of the area between the power curve and the random model to the area between a perfect model and the random model. The model produced an accuracy ratio of 65 per cent on the control sample and of 66-67 per cent for each of the years 2001, 1999 and 1998 (accounting data referred respectively to 1999, 1997 and 1996; Credit Register data referred to 2000, 1998 and 1997). The value of accuracy ratios mentioned in studies regarding other countries normally ranges between 50 and 70%.

TABLE 5: Performance of the logit model: classification rates

ECONOMIC SECTORS	Sample composition			cut-off points (%)	Classification rates (%)			
					"IN-SAMPLE"		"OUT-OF-SAMPLE"	
	No. of SOUND firms	No. of INSOLVENT firms	% INSOLVENT (on the whole sample)		SOUND	INSOLVENT	SOUND	INSOLVENT
MANUFACTURING	46,683	585	1.24	1.083	74.7	74.9	74.6	71.7
TRADE	28,949	387	1.32	1.050	75.1	74.9	75.7	73.7
CONSTRUCTION	17,282	323	1.83	1.370	72.7	72.4	72.1	70.7
SERVICES	22,915	242	1.05	0.852	75.0	74.8	75.2	81.8
Total or Mean	**115,829**	**1,537**	**1.31**		**74.6**	**74.4**	**74.6**	**73.6**

Notes:
Insolvency events: year 2000
Explanatory variables: Balance-Sheet register 1998 and Credit Register 1999

The quality distribution of loans to the 180,000 firms at the end of 2001 is shown in Table 6: 32 per cent of the total is classified in investment grade classes (probability of default lower than 0.45 per cent); another 47 per cent is included in risk classes with PD between 0.45 and 1 per cent.

Exposure at default has been computed as follows:

EAD = drawn amount + 0.75*undrawn portion of committed credit lines + CCF*other off-balance sheet items

where CCF is for each bank the average regulatory credit conversion factor for the various types of off-balance sheet items and 75% is the conversion factor used in the IRB foundation approach of the New Basel Capital Accord for commitments that are not unconditionally cancellable.

TABLE 6
Italian banks: loans to corporate borrowers by risk bucket

Risk buckets (individual PDs)			**corresponding agency ratings**	**Bank loans (%)**				
				1997	**1998**	**1999**	**2000**	**2001**
0.00	-	0.15	>= A	6.1	5.5	7.5	9.4	4.6
0.15	-	0.45	BBB	27.7	26.1	23.6	23.6	27.6
0.45	-	0.70	BB	24.0	24.6	25.9	23.6	23.9
0.70	-	1.00	BB	19.5	20.1	23.2	22.3	23.2
1.00	-	2.00	BB-	12.4	11.5	12.9	14.0	13.3
2.00	-	4.00	B+	4.7	4.6	3.4	3.4	4.2
4.00	-	8.00	B	2.9	4.4	1.9	1.9	1.7
8.00	-	16.00	B-	2.3	2.8	1.4	1.5	1.2
16.00			CCC/C	0.3	0.4	0.2	0.3	0.1
Total loans(billion euro)				**222**	**241**	**241**	**268**	**285**

Source: Bank of Italy's Credit Register and CERVED's Company Account Register

Bank loans are oustanding amounts as of year-end.
In each period borrowers are classified in risk buckets according to their probability of default within the following year.

Indications on the loss given default (LGD), that is the percentage loss the bank expects to record in the case of a borrower's insolvency, are drawn from a survey conducted by the Bank of Italy in 2000 (Bank of Italy, 2001). For each bank the average LGDs for collateralised and non collateralised lending have been considered.

5.4 Estimating Credit Value at Risk

Individual risk components allow to measure the expected loss relative to each transaction, defined as EAD*PD*LGD. The portfolio expected loss is a simple sum of the expected losses computed loan by loan; measured as a percentage of the EAD, the portfolio expected loss is the weighted sum of the individual expected losses.

To obtain the portfolio credit losses' probability density function (PDF) we use a model developed by Prometeia which relates credit default losses to macroeconomic variables.

Models which relate credit default losses to macroeconomic variables rely on the intuition, supported by empirical facts, that the frequency of defaults increases in the periods of economic downturn and vice versa. However, while the default rates for different industries tend to move together in relation to the state of the economy, the impact of macroeconomic factors on different industries/regions is different, depending upon their sensitivity to aggregate market influences. In addition, certain industries/regions undergo dynamic pressures that put them at risk due to factors that affect uniquely firms in that industry/region. This implies that managers can exploit this different cyclical sensitivity and/or sensitivity to different macroeconomic factors in order to reduce the overall credit loss uncertainty.

In general, assuming that there is no uncertainty in the recovery rate, the portfolio unexpected loss depends on the size of the exposure to a single borrower, on the volatility of the default rate and on default correlation. The lower the correlation among the default rates of different segments, the greater the potential to reduce a bank's risk exposure through diversification.

Based on these assumptions, credit risk models such as that outlined in Wilson (1997a and 1997b) and that used in this paper, developed by Prometeia[12], estimate the loss distribution by forecasting the average default rate for a particular customer segment under different economic scenarios and, for all customer segments and across all the macroeconomic scenarios, translating the estimated default rates into a distribution of losses via a Monte Carlo simulation process.

Variation in the average credit quality are explained by the unexpected changes or innovations in macroeconomic variables. The correlations between the risk segments result from the underlying macroeconomic factors and the correlation between the error terms.

The model proposed by Prometeia classifies domestic commercial borrowers into 207 segments obtained by crossing 23 industrial activity groups and 9 geographical areas and models the correlated evolution of average default rates for these segments. The parameters of the model have been estimated as to match the historical default rate variability shown by each segment.

For a given macroeconomic scenario, the conditional probability of default for each segment is then translated into a distribution of losses as in the CreditRisk+ framework[13]. For each segment, losses (exposures, net of the recovery rate) are divided into bands and it is assumed that the number of defaults in each exposure band follows a Poisson distribution and that the mean default rate is itself stochastic, reflecting the influence of macroeconomic factors. The distribution of losses in each exposure band is not derived analytically but using a Monte Carlo simulation. The total loss distribution represents the aggregation of all-scenario specific distributions in a single all-encompassing distribution[14].

[12] The model is proprietary as well as its technical documents. An outline of the model is in Botticini, Marchesi, Toffano (2000). See also the Appendix of this paper.

[13] CreditRisk+ is a trademark of Credit Suisse Financial Products (CSFP) and applies an actuarial science framework to the derivation of the loss distribution of a loan portfolio (CSFP, 1997).

[14] In each simulation, the number of defaults for each band is drawn from a Poisson distribution specified by the band's mean default rate adjusted according to a segment's mean default rate conditional to a given macroeconomic scenario. Band losses are then aggregating into the total loan loss distribution corresponding to that scenario simulation. These steps are repeated for many economic scenarios (e.g. 400,000 times as the number of simulations we used in this paper). Losses obtained in each simulation are ordered to obtain the loss corresponding to the desired percentile level.

The model allows to decompose total unexpected loss into a portion due to individual concentration risk and the portion due to systematic risk. Concentration risk is measured under the hypothesis that default events in each band are independent i.e. that mean default rates in each band are not allowed to vary over the business cycle and therefore there is not a systematic default correlations among loans. The only element of variability is given by the uncertainty, modelled with a Poisson distribution, of the default rate around the given mean default rate.

Systematic risk is the difference between the overall Credit VaR corresponding to a desired confidence level risk and the concentration risk.

6. The first set of results: are merged banks less risky at the time of the merger ?

Our first objective is to analyse whether bank mergers actually reduce credit risk by producing diversification gains[15].

For all merger operations we compute expected and unexpected losses for the loan portfolios of the acquiring, target and merged banks. The UL is calculated at the 99.9% confidence level, the same level used to calculate the risk weights in the IRB approach of the new Basel capital requirements[16].

Even though the unexpected loss or credit VaR is the appropriate measure of risk, we observed above that, given the nature of credit risk, expected losses are also an important component in the process of capital allocation. The two measures can be used for different purposes.

The portfolio's expected loss, which in turns depends on the average probability of default and on the loss given default, provides evidence on the average credit quality of borrowers. Therefore, at the time of the merger, the average default rate and the expected loss can be used to compare the credit quality of the loan portfolio of the acquiring and of the target bank. Some time after the merger, both measures can be used to assess trends in the lending policy of the merged bank.

On the other hand, the primary benefit of diversification across individuals, sectors and geographic areas comes from reducing the variance of loss; as a consequence, the portfolio's unexpected loss provides evidence of such benefits at the time of the merger and after.

[15] Dietsch and Oung (2001) perform a similar analysis estimating the pre- and post-merger risk of French banking groups using a single-factor credit risk model.
[16] In this case, the level of economic capital is set to achieve a 0.01% estimated probability that unexpected credit losses will exceed this level, thereby causing insolvency.

RESULTS AT THE TIME OF THE DEAL

TABLE 7: EXPECTED DEFAULT RATE AND EXPECTED LOSS

	Expected default rate		Expected default rate (weighted average)		Expected loss (*)	
	Acquiring bank	Target bank	Acquiring bank	Target bank	Acquiring bank	Target bank
MEAN	1.07%	1.17%	0.99%	1.17%	0.42%	0.46%
MEDIAN	1.02%	1.10%	0.88%	0.91%	0.38%	0.38%
STD	0.21%	0.38%	0.26%	0.64%	0.16%	0.26%

(*) as a percentage of portfolio exposure (EAD)

Tables 7 and A1 compare the expected default rate and the expected loss rate of the acquiring and of the target banks' credit portfolio. Tables 8 and A2 show unexpected loss rates, i.e. credit VaR at 99.9% also for the merged banks' portfolio.

Data on portfolio's expected default rates show that, on average, the quality of loan portfolio is slightly lower for the target banks than for the acquiring banks (1.17 as against 1.07 per cent) but this difference is not statistically significant (parametric and non-parametric tests are reported in Table A1a). Similarly, the propensity of the acquiring banks to finance more creditworthy borrowers shown by the difference in the weighted average default rate (1.17 vs. 0.99 per cent) is not confirmed to be statistically significant (Table A1b).

Expected loss rates are even more similar, in connection with the lower variability of the LGD figures.

For each deal, the post-merger figures of the three variables obviously lie between those of the pre-merger banks (see Table A1).

RESULTS AT THE TIME OF THE DEAL

TABLE 8: UNEXPECTED LOSS, CONCENTRATION RISK, SYSTEMATIC RISK

	Unexpected loss (*)			Concentration risk (*)			Systematic risk (*)		
	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank
MEAN	2.00%	3.31%	1.87%	1.34%	2.70%	1.23%	0.66%	0.61%	0.64%
MEDIAN	1.77%	2.37%	1.67%	1.30%	1.86%	0.98%	0.54%	0.51%	0.59%
STD	0.79%	2.35%	0.73%	0.72%	2.39%	0.74%	0.43%	0.41%	0.36%

(*) as a percentage of portfolio exposure (EAD)

Target banks are nonetheless riskier than acquiring banks: the average unexpected loss rate is 3.31 per cent compared with 2.00 per cent of the acquiring banks; the median values are 2.37 per cent and 1.77 per cent (Table 8); these differences are statistically significant (Table A2a).

The higher variability of losses for the target banks is largely driven by the concentration of the exposures on relatively few obligors: for these banks, concentration risk makes up on average 82% of the total unexpected loss. This evidence is not surprising given the average relatively small size and their nature of regional banks.

However, even for the larger, well-diversified portfolios of the acquiring banks, concentration risk accounts for two/thirds of the total unexpected variability of losses, showing a potential for a reduction in idiosyncratic (concentration) risk.

The importance of idiosyncratic risk in determining the overall variability of losses is explained by the small size of a large portion of Italian commercial and industrial companies, whose default risk is relatively less affected by trends in the economic cycle and more influenced by factors that are specific to each company.

The unexpected loss of the combined portfolios is, on average, 1.87%. However, the mean value is largely driven by one outlier, so a more robust indicator is the median, which shows a 6 per cent risk reduction compared to that of the acquiring bank. This difference is statistically significant (see non-parametric tests in Table A2a).

Table 8 also shows that the reduction in risk is due to diversification of idiosyncratic risk; this risk component is significantly statistically reduced for the post-merger portfolio (Table A2b, non parametric tests) while there is no significant statistical change in the portion of unexpected loss due to systematic risk (Table A2c).

The post-merger loan portfolio is in fact less concentrated than the acquiring bank's loan portfolio. For the post-merger portfolio, the Herfindahl index measuring the concentration of exposures at the individual borrower level is lower on average by 15% compared to the acquiring banks' portfolio; for half of the deals, the post-merger portfolio's individual loan concentration decreases by more than 20% (Tables 9 and A3).

RESULTS AT THE TIME OF THE DEAL

TABLE 9: INDIVIDUAL LOAN CONCENTRATION

	Herfindhal coefficient		
	Acquiring bank	Merged bank	Difference %
Mean	0.4188	0.3577	-14.5871
Median	0.2200	0.1751	-20.4320
Std	0.4526	0.3724	-17.7042

The Herfindahl index is defined as follows

$$100 * \sum_{i=1}^{n} x_i^2$$

where x_i is the share of the i-th borrower in the bank's loan portfolio and n is the number of borrowers.

The acquisition of new customers contributed to the diversification of idiosyncratic risk. As a result of the merger, acquiring banks record a 34 per cent average increase in the number of credit relationships. Loans to new borrowers amount to 31% of total loans before the deal (Tables 10 and A4). This evidence also shows that loans to new borrowers are approximately equally-sized distributed and therefore helped to decrease individual loan concentration.

RESULTS AT THE TIME OF THE DEAL

TABLE 10: NON-OVERLAPPING BORROWERS

	New borrowers		Exposure (EAD) of new borrowers	
	As a % of the acquiring bank's borrowers	As a % of the target bank's borrowers	As a % of the acquiring bank's exposure	As a % of the target bank's exposure
Mean	33.8	81.2	30.9	68.8
Median	23.0	87.1	20.4	76.8
Std	30.9	16.6	30.3	22.8

On the other hand, in macroeconomic multi-factor models like the one we use in this paper, potential diversification of segment-specific risk occurs if the bank expands into segments characterised by a lower volatility of average default rates because of a lower sensitivity to macro-economic factors. A second component is the expansion into segments affected by different macro-economic factors and therefore characterized by a low default rate correlation, that would also contribute to reduce the overall portfolio's variability of losses. A third component is the influence of segment-specific idiosyncratic risk on the overall volatility of that segment.

The historical volatility of the average default rate of the 23 Italian industry segments is only partially explained by the sensitivity to macro-economic factors; some 60-70% of such volatility is due to factors specific to each segment that do not depend on the state of the macro-economy (Botticini, Marchesi, and Toffano, 2000). In such a case, as portfolio diversification increases, the relative importance of segment-specific idiosyncratic risk will shrink, and the exposure of a loan portfolio to segment-specific shocks will also shrink.

Table A5 reports the Herfindahl index measuring the concentration of the various banks' portfolios into the 207 customer segments. These indexes are generally low, even if the target banks are, as expected, more concentrated. As a result of the merger, the concentration of the acquiring banks decreases on average by almost one sixth, showing that M&As included in our sample actually produced a certain increase in the portfolio diversification along the industry/region dimension, even if this diversification did not result in a reduction of variability of losses due to systematic risk.

7. The second set of results: do banks take on more risk after the merger ?

The second objective of the paper is to analyse whether merged institutions actually "misuse" diversification gains to change the composition of their portfolio towards riskier assets. As already mentioned, a deterioration of credit quality could be the result either of a strategic decision or of a less effective monitoring activity and a lack of knowledge of the new segments in which the merged banks perform their lending activity.

In the literature, the incentives to take on more risk after consolidation have been widely highlighted; however, empirical evidence confirming such hypothesis has been hardly provided.

By looking at the portfolio's loss statistics, i.e. expected default rate and expected loss rate two years after the merger we can effectively assess whether the credit quality of the loans of the merged banks has been actually worsening over time. Given the decision to focus on a post-merger two-year horizon, the sample shrinks to 22 deals, since M&As which took place after March 2001 cannot be considered[17].

As a way to control for changes in macroeconomic conditions, the obligors have been assigned the same PDs they had at the time of the merger. This allows to focus on only three sources of change in the overall quality of the portfolios: the exit of borrowers, the acquisition of new borrowers and a different distribution of loans to old customers.

If a merged bank decided to invest diversification gains into riskier assets we should observe a sharp decrease in the exposure of top quality borrowers and a low quality of newly financed firms.

The empirical evidence can be summarised as follows (Tables A6 and A7):

1. Two years after the mergers, 72.6 per cent of total exposure is granted to clients which were already financed by the same bank at the time of the deal. These are borrowers whose probabilities of default are relatively low: the median of their PDs is .99 (Table A6) as against 1.07 at the time of the deal (Table 7). Loans to these borrowers increase by 12 per cent.
2. At the time of the deal the borrowers who were dropped in the following two years accounted for 22 per cent of the borrowers by number and for 12 per cent by value (Table A7). Their median default rate was significantly higher than that of the clients the banks decided to keep: 1.39 per cent as against .99 (Table A7a for non-parametric tests).
3. Two years after the merger, lending to new customers accounts for 27.4 per cent of the portfolio total exposure. The median probabilities of default of newly financed firms is 1.29 per cent, lower than that of the dropped borrowers (1.39 per cent); this difference is statistically significant only at 7 per cent level (Table A7b, median sign test).

To sum up, changes in the composition of loan portfolios seem to suggest that, after M&A deals, Italian banks choose to pursue an overall improvement in the credit quality of their corporate loan portfolios by keeping the relationships with the most creditworthy borrowers and changing the composition of the rest of the portfolio towards clients of a better quality.

Given that the large majority of loans continue to be granted to the same borrowers, on average the portfolio's expected default rate does not change much two years after the merger (Table A8); the median value of the weighted average expected default rate decreases from .95 to .87 per cent.

The impact of post-merger lending policies on credit risk is shown in Table 11 and A9. Table A9a reports statistical tests.

[17] In one case we considered a post-merger horizon of one-year and a half.

RESULTS TWO YEARS AFTER THE MERGER

TABLE 11: UNEXPECTED LOSS, CONCENTRATION RISK, SYSTEMATIC RISK

	Unexpected loss (*)		Concentration risk (*)		Systematic risk (*)	
	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years
MEAN	1.89%	1.92%	1.25%	1.35%	0.64%	0.56%
MEDIAN	1.67%	1.74%	1.00%	1.18%	0.61%	0.46%
STD	0.75%	0.63%	0.80%	0.65%	0.38%	0.39%

(*) as a percentage of portfolio exposure (EAD)

The portion of unexpected loss due to systematic risk is lower two years after the merger: on average it decreases from 0.64 to 0.56 per cent; the difference is more pronounced for the median, from 0.61 per cent to 0.46 per cent. In fact, the median sign test is significant at 6 per cent level (Table A9a). This evidence seems to show that post-merger policies by banks included in our sample exploited some additional potential for diversification of segment-specific risk by expanding into less volatile segments and/or into segments affected by different macro-economic factors.

Effectively, the Herfindahl index measuring the concentration of the various banks' portfolios into the 207 customer segments decreases slightly two years after the merger. The average index reduces from 4.2 to 3.9 (Table A10).

On the other hand, concentration risk increases on average by 8 per cent, from 1.25 to 1.35 per cent; the median value from 1.00 per cent to 1.18 per cent, but these difference are not statistically significant.

The changes of these two risk components produce an off-setting effect on the total variability of loss; statistical tests show that there is no significant difference between merged banks' average loan portfolio unexpected losses at the time of the deal and two years after.

In sum, there is no evidence to support the hypothesis that merged banks tend to engage into risky strategies and that credit risk of their loan portfolio increases as a consequence of these strategies.

On the contrary, our evidence shows an increase in lending to more creditworthy borrowers and an increased diversification of systematic risk.

8. Concluding remarks

In this paper we examine the effects of the consolidation process in the Italian banking market on credit risk. For a sample of M&As which took place in the period 1997-2001 we measure the main statistics derived from the pre- and post- merger probability density function of credit losses for the C&I portfolio of the acquiring banks. The aim is to quantify the diversification gains arising from merger operations that are usually mentioned in the M&As literature but has never been, to our knowledge, properly measured. Our paper, as well as the paper by Dietsch and Oung (2001), is the first study to apply a portfolio approach to measuring credit risk in a M&A framework.

We find that, as a consequence of a merger, credit risk is significantly reduced because of diversification of idiosyncratic risk. The importance of idiosyncratic risk in determining the overall variability of credit losses in Italian banks' loan portfolio is explained by the small size of a large portion of Italian commercial and industrial companies, whose default risk is relatively less affected by trends in the economic cycle and more influenced by factors that are specific to each company.

The paper also provides a detailed analysis of how the composition of bank credit portfolios has changed two years after the consolidation. This analysis is meant to test the hypothesis, frequently mentioned in the M&As literature, that merged banks tend to pursue risky strategies resulting in an increase of their probability of default and, in turn, of systemic risk. We examine whether merged banks in Italy shifted the composition of their credit portfolios towards less creditworthy borrowers and the effect of post-merger credit policies on portfolio's risk.

Our empirical evidence does not support such hypothesis, since the merged banks decide to keep credit relationships with high quality obligors and close those with risky borrowers. Moreover, our findings show no change in the overall unexpected variability of losses and an increased diversification of systematic risk.

Future work is needed to check the robustness of the results concerning the banks' post-merger credit policies. First, we need to compare these results with the portfolio's risk profile of banks in a control sample. A second exercise would assess the actual risk of banks two years after the merger using current PDs, and decomposing the influence on risk of changes in PDs from that of changes in exposures.

References

Acharya, V. (2001), A Theory of Systemic Risk and Design of Prudential Bank Regulation, paper presented the "Banks and Systemic Risk Conference", Bank of England, 23-25 May.

Acharya, V., Hasan, I. and Saunders, A. (2002), Should banks be diversified? Evidence from individual bank loan portfolios, BIS Working Papers, No 118, September.

Amihud, Y. and Miller, G. (1998), Bank Mergers & Acquisitions, Kluwer Academic Publishers.

Alexander, C. ed. (1999), Risk Management and Analysis, Vol. I, John Wiley & Sons.

Bank of Italy (2001), Annual Report for the year 2000 (abridged version), Rome, 31 May.

Benston, G. J., Hunter, W.C., and Wall, L.D. (1995), Motivations for Bank Mergers and Acquisitions: Enhancing the Deposit Insurance Put Option versus Earnings Diversification, Journal of Money, Credit and Banking, vol. 27, No 3, August, pp. 777-88.

Berger, A.N., Demsetz, R., and Strahan, P.E. (1999), The consolidation of the financial services industry: Causes, consequences and implications for the future, Journal of Banking and Finance, Nos 2-4, February, pp. 135-194.

Berger, A.N. (1998), The efficiency effects of bank mergers and acquisition: A preliminary look at the 1990s data, in Amihud, Y. and Miller, G. (1998).

Bikker, J.A., van Lelyveld I.P.P. (2002), Economics versus regulatory capital for financial conglomerates, De Nederlandsche Bank, Research Series Supervision, no. 45, April.

Boyd, J.H., Graham, S.L. (1998), Consolidation in US banking: Implications for efficiency and risk, in Amihud, Y. and Miller, G. (1998).

Botticini A., Marchesi and M., Toffano C. (2000), Un modello di stima delle correlazioni tra le probabilità di insolvenza per il portafoglio di una banca commerciale, in La gestione del rischio di credito, Savona P. and Sironi A. ed., EDIBANK, Bancaria Editrice.

Cannata, F., Fabi, F., and Laviola, S. (2002), Rating interni e sistemi di gestione del rischio di credito: la misurazione della probabilità di insolvenza, Bancaria, April.

Cerasi. V. and Daltung, S. (2000), The Optimal Size of a Bank: Costs and Benefits of Diversification, European Economic Review, Vol. 44, No 9, October.

Craig, B. and Cabral dos Santos, J. (1997), The Risk Effects of Bank Acquisitions, Federal Reserve Bank of Cleveland, Economic Review, 2nd Quarter.

Crouhy, M., Galai D. and Mark R. (2000), A comparative analysis of current credit risk models, Journal of Banking and Finance, 24, 59-117.

CSFP (1997), CreditRisk+: A Credit Risk Management Framework, London

De Nicolò, G. (2000), Size, Charter Value and Risk in Banking: An International Perspective, International Finance Discussion Paper, No 689, December.

De Nicolò, G. and Kwast, M. (2002), Systemic risk and financial consolidation: Are they related?, Journal of Banking and Finance, Vol. 26, No 5, May.

Demsetz, R.S. and Strahan, P.E. (1997), Diversification, Size, and Risk at Bank Holding Companies, Journal of Money, Credit and Banking, 29, pp. 300-313.

Dietsch, M. and Oung, V. (2001), The Formation of Large Banking Groups in France: Observed and Potential Effects on Costs, Income end Risks, in Bulletin de la Commission bancaire, N. 25, November.

Federal Reserve Bank of New York (2000), Specialization, Diversification, and the Structure of the Financial System: the Impact of Technological Change and Regulatory Reform, Economic Policy Review, Vol. 6, No. 4, October

Foglia, A., Iannotti, S., and Marullo Reedtz, P. (2001), The Definition of the Grading Scales in Banks' Internal Rating Systems, Monte dei Paschi di Siena, Economic Notes, vol. 30, No 3, pp 421-456.

Gorton, G. and Winton, A. (2002), Financial Intermediation, NBER, Working Paper 8928, May.

Group of Ten (2001), Report on Consolidation in the Financial Sector, Bank for International Settlements.

Hughes, J.P:, Lang, W.W., Mester, L.J., and Moon, C. (1999), The dollars and sense of bank consolidation, Journal of Banking and Finance, Nos 2-4, February, pp. 291-324.

Hughes, J.P., Mester, L.J., and Moon, C. (2001), Are scale economies in banking elusive or illusive? Evidence obtained by incorporating capital structure and risk-taking into models of bank production, Journal of Banking and Finance, No 12, December, 2169-2208.

Jones, D. and Mingo, J. (1999), Credit Risk Modeling and Internal Capital Allocation Processes: Implications for a Models-Based Regulatory Bank Capital Standard, Journal of Economic and Business, 51, 79-108.

Markovitz, H (1952), Portfolio Selection, Journal of Finance, no.7, March.

Markovitz, H. (1959), Portfolio Selection: Efficient Diversification of Investments, New York: John Wiley & Sons.

Mishkin, F.S. (1999), Financial consolidation: Dangers and opportunities, Journal of Banking and Finance, Nos 2-4, February, pp. 675-691.

Mishkin, F.S. (1998), Bank consolidation: A central banker's perspective, in Amihud, Y. and Millere, G. (1998).

Ong, M.K. (1999), Capital Allocation and Performance Measurement, Risk Books.

Paroush, J. (1995), The Effect of Merger and Acquisition Activity on the Safety and Soundness of a Banking System, Review of Industrial Organization, Vol. 10, No 1, February

Saunders, A. (1999), Credit Risk Measurement, John Wiley & Sons.

Shaffer, S. (1989) Pooling Intensifies Joint-Failure Risk, Federal Reserve Bank of Philadelphia, Working Paper No 89-01, January.

Tsatsaronis, K. (2002), Systemic financial risk and macro-prudential supervision, Bank for International Settlements, mimeo.

Wilson, T. (1997a), Portfolio credit risk (1), Risk Magazine, September .

Wilson, T. (1997b), Portfolio credit risk (2), Risk Magazine, October.

Winton, A. (1999), Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending, University of Minnesota.

RESULTS AT THE TIME OF THE DEAL

TABLE A1: EXPECTED DEFAULT RATE AND EXPECTED LOSS

Merger identification number	Expected default rate			Expected default rate (weighted average)			Expected loss (*)		
	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank
1	1,14%	0,69%	1,14%	1,02%	0,47%	0,82%	0,28%	0,18%	0,24%
2	0,87%	1,53%	1,01%	0,65%	1,09%	0,72%	0,17%	0,46%	0,22%
3	1,38%	0,94%	1,31%	1,21%	0,88%	1,16%	0,85%	0,49%	0,80%
4	1,25%	1,01%	1,20%	1,03%	0,87%	0,98%	0,45%	0,35%	0,42%
5	1,76%	1,23%	1,69%	1,99%	1,03%	1,80%	0,81%	0,39%	0,73%
6	1,02%	2,42%	1,19%	0,89%	3,05%	1,08%	0,38%	1,07%	0,44%
7	1,22%	1,12%	1,25%	1,12%	0,90%	1,11%	0,43%	0,39%	0,44%
7	1,22%	2,16%	1,25%	1,12%	3,43%	1,11%	0,43%	1,39%	0,44%
8	0,96%	0,87%	0,95%	0,86%	0,88%	0,86%	0,34%	0,35%	0,34%
8	0,96%	0,78%	0,95%	0,86%	0,77%	0,86%	0,34%	0,29%	0,34%
9	0,96%	1,10%	1,05%	0,82%	0,69%	0,77%	0,33%	0,30%	0,32%
10	1,03%	1,01%	1,07%	0,87%	0,90%	0,88%	0,37%	0,38%	0,37%
11	0,88%	0,90%	0,89%	0,76%	0,69%	0,74%	0,33%	0,30%	0,32%
12	1,31%	0,81%	1,24%	1,27%	0,75%	1,05%	0,55%	0,28%	0,43%
13	1,17%	1,23%	1,20%	0,88%	1,49%	1,05%	0,36%	0,67%	0,45%
14	1,11%	1,28%	1,11%	0,91%	1,00%	0,92%	0,70%	0,37%	0,65%
15	1,16%	1,13%	1,16%	1,00%	0,78%	0,88%	0,71%	0,25%	0,44%
16	1,17%	1,47%	1,28%	0,86%	1,57%	1,03%	0,44%	0,69%	0,50%
17	0,99%	0,92%	0,97%	0,83%	0,86%	0,84%	0,34%	0,38%	0,35%
18	0,92%	0,91%	0,93%	0,99%	0,86%	0,98%	0,44%	0,38%	0,42%
19	0,95%	1,72%	1,07%	0,97%	1,58%	1,13%	0,39%	0,57%	0,44%
20	0,92%	1,09%	0,95%	0,76%	1,08%	0,86%	0,32%	0,10%	0,26%
21	0,88%	0,83%	0,87%	0,81%	0,93%	0,85%	0,34%	0,37%	0,35%
22	0,87%	0,92%	0,88%	0,78%	0,79%	0,78%	0,32%	0,33%	0,32%
23	1,13%	1,16%	1,17%	1,24%	0,99%	1,14%	0,51%	0,18%	0,38%
23	1,13%	1,17%	1,17%	1,24%	1,18%	1,14%	0,51%	0,62%	0,38%
24	0,92%	1,43%	0,99%	0,84%	2,22%	0,96%	0,37%	0,74%	0,40%
25	1,32%	1,46%	1,34%	1,34%	1,19%	1,32%	0,54%	0,51%	0,53%
26	1,36%	1,27%	1,35%	1,47%	1,35%	1,41%	0,54%	0,57%	0,55%
27	0,78%	1,07%	0,82%	0,79%	0,90%	0,81%	0,44%	0,35%	0,43%
28	0,68%	0,67%	0,68%	0,77%	0,66%	0,72%	0,16%	0,25%	0,20%
29	0,86%	1,44%	1,03%	0,79%	1,75%	0,92%	0,25%	0,69%	0,31%
30	0,92%	0,94%	0,93%	0,85%	0,91%	0,88%	0,31%	0,39%	0,35%
MEAN	1,07%	1,17%	1,09%	0,99%	1,17%	0,99%	0,42%	0,46%	0,41%
MEDIAN	1,02%	1,10%	1,07%	0,88%	0,91%	0,92%	0,38%	0,38%	0,40%
STD	0,21%	0,38%	0,19%	0,26%	0,64%	0,22%	0,16%	0,26%	0,13%

(*) as a percentage of portfolio exposure (EAD)

RESULTS AT THE TIME OF THE DEAL

TABLE A2: UNEXPECTED LOSS, CONCENTRATION RISK, SYSTEMATIC RISK

Merger identification number	Unexpected loss (*)			Concentration risk (*)			Systematic risk (*)		
	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank	Acquiring bank	Target bank	Merged bank
1	1,46%	6,91%	3,45%	1,35%	6,87%	3,38%	0,10%	0,04%	0,07%
2	1,49%	2,20%	1,58%	1,31%	1,71%	1,38%	0,18%	0,49%	0,20%
3	2,93%	2,13%	2,67%	1,36%	1,54%	1,14%	1,58%	0,59%	1,53%
4	1,71%	1,48%	1,58%	1,35%	0,82%	1,19%	0,36%	0,66%	0,39%
5	1,20%	2,36%	1,67%	0,65%	1,86%	0,98%	0,54%	0,50%	0,69%
6	1,87%	4,41%	1,79%	1,30%	3,80%	1,21%	0,57%	0,61%	0,58%
7	1,49%	1,66%	1,33%	1,35%	1,32%	1,01%	0,14%	0,34%	0,32%
7	1,49%	5,98%	1,33%	1,35%	4,39%	1,01%	0,14%	1,59%	0,32%
8	1,18%	1,57%	1,14%	0,81%	0,97%	0,72%	0,37%	0,60%	0,42%
8	1,18%	3,66%	1,14%	0,81%	3,48%	0,72%	0,37%	0,19%	0,42%
9	1,30%	2,25%	1,29%	0,97%	1,93%	0,91%	0,32%	0,32%	0,39%
10	1,55%	1,57%	1,26%	1,27%	1,12%	0,80%	0,28%	0,45%	0,46%
11	1,15%	2,37%	1,13%	0,68%	2,01%	0,59%	0,47%	0,36%	0,54%
12	2,37%	2,23%	1,70%	0,84%	1,98%	0,87%	1,52%	0,25%	0,83%
13	2,50%	2,13%	1,95%	2,43%	1,40%	1,88%	0,08%	0,73%	0,08%
14	3,42%	10,25%	3,09%	2,40%	9,89%	2,24%	1,02%	0,35%	0,84%
15	3,04%	2,80%	2,01%	2,25%	2,51%	1,42%	0,80%	0,29%	0,59%
16	2,05%	2,59%	1,84%	1,52%	1,37%	1,15%	0,53%	1,22%	0,69%
17	1,71%	1,28%	1,43%	0,72%	0,93%	0,49%	0,99%	0,35%	0,94%
18	1,86%	2,43%	1,83%	0,56%	1,70%	0,53%	1,30%	0,72%	1,30%
19	1,69%	2,88%	1,84%	0,68%	2,05%	0,93%	1,01%	0,84%	0,91%
20	1,19%	0,60%	0,96%	0,75%	0,45%	0,61%	0,44%	0,15%	0,35%
21	3,21%	1,96%	2,38%	2,79%	1,26%	1,98%	0,41%	0,69%	0,41%
22	1,99%	2,53%	1,82%	1,78%	2,25%	1,64%	0,21%	0,29%	0,18%
23	2,08%	1,58%	1,61%	0,98%	1,40%	0,70%	1,09%	0,18%	0,90%
23	2,08%	4,44%	1,61%	0,98%	2,69%	0,70%	1,09%	1,75%	0,90%
24	1,15%	10,33%	1,30%	0,45%	10,10%	0,92%	0,70%	0,23%	0,38%
25	4,35%	4,38%	4,02%	3,68%	3,73%	3,38%	0,67%	0,65%	0,64%
26	3,12%	5,73%	3,27%	1,81%	5,22%	2,43%	1,31%	0,51%	0,85%
27	3,05%	5,90%	2,83%	1,82%	5,17%	1,61%	1,23%	0,73%	1,22%
28	1,90%	2,18%	1,67%	1,41%	1,24%	0,94%	0,49%	0,94%	0,73%
29	1,58%	2,54%	1,61%	0,84%	1,44%	0,74%	0,73%	1,09%	0,87%
30	1,77%	1,99%	1,72%	1,09%	0,64%	0,54%	0,69%	1,35%	1,17%
MEAN	2,00%	3,31%	1,87%	1,34%	2,70%	1,23%	0,66%	0,61%	0,64%
MEDIAN	1,77%	2,37%	1,67%	1,30%	1,86%	0,98%	0,54%	0,51%	0,59%
STD	0,79%	2,35%	0,73%	0,72%	2,39%	0,74%	0,43%	0,41%	0,36%

(*) as a percentage of portfolio exposure (EAD)

RESULTS AT THE TIME OF THE DEAL
TABLE A1a: EXPECTED DEFAULT RATE - Statistical tests

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: EXPECTED DEFAULT RATE
ACQUIRING BANKS VS. TARGET BANKS

Wilcoxon Scores (Rank Sums) for Variable edf
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	1052,0	1105,5	77,973516	31,878788
PASSIVA	33	1159,0	1105,5	77,973516	35,121212

Wilcoxon Two-Sample Test

Statistic	1052,000
Normal Approximation Z	-0,6797
One-Sided Pr < Z	0,2483
Two-Sided Pr > !Z!	0,4967
t Approximation	
One-Sided Pr < Z	0,2495
Two-Sided Pr > !Z!	0,4991

Z includes a continuity correction of 0.5.

Median Scores (Number of Points Above Median) for Variable edf
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	15,0	16,5	2,046573	0,454545
PASSIVA	33	18,0	16,5	2,046573	0,545455

Median Two-Sample Test

Statistic	15,000
Z	-0,7329
One-Sided Pr < Z	0,2318
Two-Sided Pr > !Z!	0,4636

Van der Waerden Scores (Normal) for Variable edf
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-2,803413	0,0	3,87061	-0,084952
PASSIVA	33	-2,803413	0,0	3,87061	-0,084952

Van der Waerden Two-Sample Test

Statistic	-2,8034
Z	-0,7243
One-Sided Pr < Z	0,2344
Two-Sided Pr > !Z!	0,4689

Savage Scores (Exponential) for Variable edf
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-5,56869	0,0	3,942242	-0,168748
PASSIVA	33	-5,56869	0,0	3,942242	-0,168748

Savage Two-Sample Test

Statistic	-5,5687
Z	-1,4126
One-Sided Pr < Z	0,0789
Two-Sided Pr > !Z!	0,1578

TESTS ON THE EQUALITY OF MEANS
VARIABLE: EXPECTED DEFAULT RATE
ACQUIRING BANKS VS. TARGET BANKS

The TTEST Procedure

T-Test

Variable	Method	Variances	DF	t Value	Pr > !t!
edf	Pooled	Equal	64	-1,36	0,1771
edf	Satterthwaite	Unequal	50,1	-1,36	0,1784

Equality of Variances

Variable	Method	Num DF	Den DF	F Value	Pr > F
edf	Folded F	32	32	3,22	0,0014

RESULTS AT THE TIME OF THE DEAL

TABLE A1b: EXPECTED DEFAULT RATE (weighted average) - Statistical tests

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: EXPECTED DEFAULT RATE (weighted average)
ACQUIRING BANKS VS. TARGET BANKS

Wilcoxon Scores (Rank Sums) for Variable edfmp
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	1039,0	1105,5	77,973516	31,484848
PASSIVA	33	1172,0	1105,5	77,973516	35,545452

Wilcoxon Two-Sample Test

Statistic	1039,000
Normal Approximation Z	-0,8464
One-Sided Pr < Z	0,1987
Two-Sided Pr > !Z!	0,3973
t Approximation	
One-Sided Pr < Z	0,2002
Two-Sided Pr > !Z!	0,4004

Z includes a continuity correction of 0.5.

Median Scores (Number of Points Above Median) for Variable edfmp
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	15,0	16,5	2,046573	0,454545
PASSIVA	33	18,0	16,5	2,046573	0,545455

Median Two-Sample Test

Statistic	15,000
Z	-0,7329
One-Sided Pr < Z	0,2318
Two-Sided Pr > !Z!	0,4636

Van der Waerden Scores (Normal) for Variable edfmp
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-3,145312	0,0	3,870584	-0,095312
PASSIVA	33	-3,145312	0,0	3,870584	-0,095312

Van der Waerden Two-Sample Test

Statistic	-3,1453
Z	-0,8126
One-Sided Pr < Z	0,2082
Two-Sided Pr > !Z!	0,4164

Savage Scores (Exponential) for Variable edfmp
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-5,792804	0,0	3,942165	-0,175540
PASSIVA	33	5,792804	0,0	3,942165	0,175540

Savage Two-Sample Test

Statistic	-5,7928
Z	-1,4694
One-Sided Pr < Z	0,0709
Two-Sided Pr > !Z!	0,1417

TESTS ON THE EQUALITY OF MEANS
VARIABLE: EXPECTED DEFAULT RATE (weighted average)
ACQUIRING BANKS VS. TARGET BANKS

The TTEST Procedure

T-Test

Variable	Method	Variances	DF	t Value	Pr > !t!
edfmp	Pooled	Equal	64	-1,47	0,1454
edfmp	Satterthwaite	Unequal	42,5	-1,47	0,1479

Equality of Variances

Variable	Method	Num DF	Den DF	F Value	Pr > F
edfmp	Folded F	32	32	5,92	<.0001

RESULTS AT THE TIME OF THE DEAL
TABLE A2a: UNEXPECTED LOSS - Statistical tests

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: UNEXPECTED LOSS
ACQUIRING BANKS VS. TARGET BANKS

Wilcoxon Scores (Rank Sums) for Variable PINA
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	869,0	1105,5	77,973516	26,333333
PASSIVA	33	1342,0	1105,5	77,973516	40,666667

Wilcoxon Two-Sample Test

Statistic	869,000
Normal Approximation Z	-3,0267
One-Sided Pr < Z	0,0012
Two-Sided Pr > !Z!	0,0025
t Approximation	
One-Sided Pr < Z	0,0018
Two-Sided Pr > !Z!	0,0035

Z includes a continuity correction of 0.5.

Median Scores (Number of Points Above Median) for Variable PINA
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	9,0	16,5	2,046573	0,272727
PASSIVA	33	24,0	16,5	2,046573	0,727273

Median Two-Sample Test

Statistic	9,000
Z	-3,6647
One-Sided Pr < Z	0,0001
Two-Sided Pr > !Z!	0,0002

Van der Waerden Scores (Normal) for Variable PINA
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-11,693152	0,0	3,870403	-0,354338
PASSIVA	33	-11,693152	0,0	3,870403	-0,354338

Van der Waerden Two-Sample Test

Statistic	-11,6932
Z	-3,0212
One-Sided Pr < Z	0,0013
Two-Sided Pr > !Z!	0,0025

Savage Scores (Exponential) for Variable PINA
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-11,95354	0,0	3,942295	-0,362228
PASSIVA	33	-11,95354	0,0	3,942295	-0,362228

Savage Two-Sample Test

Statistic	-11,9535
Z	-3,0321
One-Sided Pr < Z	0,0012
Two-Sided Pr > !Z!	0,0024

TESTS ON THE EQUALITY OF MEANS
VARIABLE: UNEXPECTED LOSS
ACQUIRING BANKS VS. TARGET BANKS

The TTEST Procedure

T-Test

Variable	Method	Variances	DF	t Value	Pr > !t!
PINA	Pooled	Equal	64	-3,04	0,0035
PINA	Satterthwaite	Unequal	39,2	-3,04	0,0042

Equality of Variances

Variable	Method	Num DF	Den DF	F Value	Pr > F
PINA	Folded F	32	32	8,76	<.0001

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: UNEXPECTED LOSS
ACQUIRING BANKS: PRE- AND POST-MERGER

Variable: DIFAF

N	33	Sum Weights	33
Mean	0,001291	Sum Observations	0,42611
Std Deviation	0,004822	Variance	2,33E-05
Skewness	-2,518784	Kurtosis	11,77208
Uncorrected SS	0,000799	Corrected SS	0,000744
Coeff Variation	373,4409	Std Error Mean	0,000839

Basic Statistical Measures

Location		Variability	
Mean	0,001291	Std Deviation	0,00482
Median	0,001610	Variance	2,33E-05
Mode	0,000363	Range	0,03033
		Interquartile Range	0,00268

Tests for Location: Mu0=0

Test	Statistic		p Value	
Student's t	t	1,538279	Pr > !t!	0,1338
Sign	M	9,5	Pr >= !M!	0,0013
Signed Rank	S	168,5	Pr >= !S!	0,0015

RESULTS AT THE TIME OF THE DEAL
TABLE A2b: CONCENTRATION RISK- Statistical tests

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: CONCENTRATION RISK
ACQUIRING BANKS VS. TARGET BANKS

Wilcoxon Scores (Rank Sums) for Variable conc
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	858	1105,5	77,97352	26
PASSIVA	33	1353	1105,5	77,97352	41

Wilcoxon Two-Sample Test

Statistic	858,0000
Normal Approximation Z	-3,1677
One-Sided Pr < Z	0,0008
Two-Sided Pr > !Z!	0,0015
t Approximation	
One-Sided Pr < Z	0,0012
Two-Sided Pr > !Z!	0,0023

Z includes a continuity correction of 0.5.

Median Scores (Number of Points Above Median) for Variable conc
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	10	16,5	2,046573	0,303030
PASSIVA	33	23	16,5	2,046573	0,696970

Median Two-Sample Test

Statistic	10,0000
Z	-3,1760
One-Sided Pr < Z	0,0007
Two-Sided Pr > !Z!	0,0015

Van der Waerden Scores (Normal) for Variable conc
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-12,226951	0	3,870571	-0,37051
PASSIVA	33	12,226951	0	3,870571	0,370514

Van der Waerden Two-Sample Test

Statistic	-12,2270
Z	-3,1590
One-Sided Pr < Z	0,0008
Two-Sided Pr > !Z!	0,0016

Savage Scores (Exponential) for Variable conc
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	-12,655976	0	3,942294	-0,383514
PASSIVA	33	12,655976	0	3,942294	0,383514

Savage Two-Sample Test

Statistic	-12,656
Z	-3,2103
One-Sided Pr < Z	0,0007
Two-Sided Pr > !Z!	0,0013

TESTS ON THE EQUALITY OF MEANS
VARIABLE: CONCENTRATION RISK
ACQUIRING BANKS VS. TARGET BANKS

The TTEST Procedure

Variable	Method	Variances	DF	t Value	Pr > !t!
conc	Pooled	Equal	64	-3,13	0,0026
conc	Satterthwaite	Unequal	37,7	-3,13	0,0033

Equality of Variances

Variable	Method	Num DF	Den DF	F Value	Pr > F
conc	Folded F	32	32	11,14	<.0001

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: CONCENTRATION RISK
ACQUIRING BANKS: PRE- AND POST-MERGER

Variable: DIFAF

N	33	Sum Weights	33
Mean	0,001093	Sum Observations	0,036075
Std Deviation	0,004929	Variance	2,43E-05
Skewness	-2,630233	Kurtosis	10,78588
Uncorrected SS	0,000817	Corrected SS	0,000778
Coeff Variation	450,9125	Std Error Mean	0,000858

Basic Statistical Measures

Location		Variability	
Mean	0,001093	Std Deviation	0,00493
Median	0,001591	Variance	2,43E-05
Mode	0,000884	Range	0,02856
		Interquartile Range	0,00274

Tests for Location: Mu0=0

Test	Statistic		p Value	
Student's t	t	1,273986	Pr > !t!	0,2118
Sign	M	9,5	Pr >= !M!	0,0013
Signed Rank	S	149,5	Pr >= !S!	0,0056

RESULTS AT THE TIME OF THE DEAL
TABLE A2c: SYSTEMATIC RISK- Statistical tests

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: SYSTEMATIC RISK
ACQUIRING BANKS VS. TARGET BANKS

Wilcoxon Scores (Rank Sums) for Variable sistem
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	1143	1105,5	77,9727	34,63636
PASSIVA	33	1068	1105,5	77,9727	32,36364

Wilcoxon Two-Sample Test

Statistic	1143,0000
Normal Approximation Z	0,4745
One-Sided Pr < Z	0,3176
Two-Sided Pr > !Z!	0,6351
t Approximation	
One-Sided Pr < Z	0,3184
Two-Sided Pr > !Z!	0,6367

Z includes a continuity correction of 0.5.

Van der Waerden Scores (Normal) for Variable sistem
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	1,13563	0	3,870352	0,034413
PASSIVA	33	-1,13563	0	3,870352	-0,03441

Van der Waerden Two-Sample Test

Statistic	1,1356
Z	0,2934
One-Sided Pr < Z	0,3846
Two-Sided Pr > !Z!	0,7692

Median Scores (Number of Points Above Median) for Variable sistem
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	17	16,5	2,046573	0,51515
PASSIVA	33	16	16,5	2,046573	0,48485

Median Two-Sample Test

Statistic	17,0000
Z	0,2443
One-Sided Pr < Z	0,4035
Two-Sided Pr > !Z!	0,8070

Savage Scores (Exponential) for Variable sistem
Classified by Variable TIPOB

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
ATTIVA	33	0,934156	0	3,942137	0,02831
PASSIVA	33	-0,934156	0	3,942137	-0,0283

Savage Two-Sample Test

Statistic	0,9342
Z	0,237
One-Sided Pr < Z	0,4063
Two-Sided Pr > !Z!	0,8127

TESTS ON THE EQUALITY OF MEANS
VARIABLE: SYSTEMATIC RISK
ACQUIRING BANKS VS. TARGET BANKS

T-Test

Variable	Method	Variances	DF	t Value	Pr > !t!
sistem	Pooled	Equal	64	0,5	0,6211
sistem	Satterthwaite	Unequal	63,9	0,5	0,6211

Equality of Variances

Variable	Method	Num DF	Den DF	F Value	Pr > F
sistem	Folded F	32	32	1,07	0,8442

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: SYSTEMATIC RISK
ACQUIRING BANKS: PRE- AND POST-MERGER

Variable: DIFAF

N	33	Sum Weights	33
Mean	0,000198	Sum Observations	0,006535
Std Deviation	0,002113	Variance	4,46E-06
Skewness	0,899504	Kurtosis	3,00608
Uncorrected SS	0,000144	Corrected SS	0,000143
Coeff Variation	1067,007	Std Error Mean	0,000368

Basic Statistical Measures

Location		Variability	
Mean	0,0002	Std Deviation	0,00211
Median	-0,00002	Variance	4,46E-06
Mode	-0,0018	Range	0,0118
		Interquartile Range	0,00156

Tests for Location: Mu0=0

Test	Statistic		p Value	
Student's t	t	0,538381	Pr > !t!	0,5940
Sign	M	-0,5	Pr >= !M!	1,0000
Signed Rank	S	11	Pr >= !S!	0,8477

RESULTS AT THE TIME OF THE DEAL

TABLE A3: INDIVIDUAL LOAN CONCENTRATION

Merger identification number	Herfindhal coefficient		
	Acquiring bank	Merged bank	Difference %
1	0,3866	1,2795	230,9374
2	0,7369	0,6198	-15,8890
3	0,1011	0,0843	-16,6073
4	0,2292	0,1593	-30,5085
5	0,2051	0,2096	2,2181
6	0,3213	0,2820	-12,2359
7	0,1918	0,1340	-30,1386
8	0,1224	0,1051	-14,0972
9	0,1380	0,1700	23,1561
10	0,2691	0,1579	-41,3217
11	0,1440	0,1213	-15,7274
12	0,1616	0,1796	11,1276
13	0,4265	0,2975	-30,2479
14	0,4337	0,4920	13,4407
15	0,4766	0,3431	-28,0051
16	0,3584	0,2352	-34,3599
17	0,1216	0,0780	-35,8397
18	0,0852	0,0813	-4,5404
19	0,0983	0,1328	35,0495
20	0,1834	0,1705	-7,0136
21	0,7662	0,4227	-44,8380
22	0,7913	0,6891	-12,9139
23	0,2108	0,1495	-29,0720
24	0,0823	0,1086	31,9215
25	1,9445	1,6405	-15,6320
26	0,7258	0,8537	17,6295
27	0,6540	0,5719	-12,5566
28	1,8001	0,7235	-59,8086
29	0,2032	0,1637	-19,4569
30	0,1938	0,0741	-61,7634
Mean	0,4188	0,3577	-14,5871
Median	0,2200	0,1751	-20,4320
Std	0,4526	0,3724	-17,7042

Note: the Herfindahl index is defined as follows

$$100 \quad * \sum_{i=1}^{n} x_i^2$$

where x_i is the share of the i-th borrower in the bank's loan portfolio and n is the number of borrowers.

RESULTS AT THE TIME OF THE DEAL

TABLE A4: NON-OVERLAPPING BORROWERS

Merger identification number	New borrowers		Exposure (EAD) of new borrowers	
	As a % of the acquiring bank's borrowers	As a % of the target bank's borrowers	As a % of the acquiring bank's exposure	As a % of the target bank's exposure
1	2,0	44,8	9,4	16,3
2	21,8	83,9	8,6	48,3
3	19,7	81,3	12,0	62,1
4	39,3	70,5	26,1	51,1
5	17,1	72,1	10,2	42,9
6	13,9	96,4	8,7	87,4
7	46,5	73,7	15,7	49,4
8	12,6	61,9	5,6	42,3
9	35,3	58,2	19,7	32,8
10	69,5	72,9	39,3	52,4
11	31,4	85,5	21,1	76,7
12	17,2	90,9	67,2	87,3
13	58,2	88,4	28,2	70,1
14	1,0	73,6	14,2	82,9
15	24,3	92,5	115,0	83,7
16	55,0	94,4	26,6	83,4
17	47,4	93,3	43,3	88,0
18	3,7	38,7	2,7	30,5
19	17,9	97,3	26,8	77,0
20	17,4	87,1	31,0	72,4
21	51,8	97,2	36,5	88,7
22	7,8	66,3	4,7	50,6
23	24,3	56,5	43,6	49,0
24	14,4	99,5	9,6	98,5
25	16,7	100,0	9,6	100,0
26	45,4	87,0	75,6	89,6
28	14,5	90,1	16,6	88,0
28	119,2	89,8	67,1	79,0
29	36,1	92,9	13,6	85,9
30	134,5	98,5	119,8	96,2
Mean	33,8	81,2	30,9	68,8
Median	23,0	87,1	20,4	76,8
Std	30,9	16,6	30,3	22,8

RESULTS AT THE TIME OF THE DEAL

TABLE A5: DIVERSIFICATION BY INDUSTRIAL/GEOGRAPHIC SEGMENT

Merger identification number	Herfindhal coefficient		
	Acquiring bank	Target bank	Merged bank
1	2,3	6,4	2,7
2	2,6	1,7	2,1
3	2,2	4,1	2,0
4	1,6	2,4	1,5
5	2,8	2,4	2,2
6	4,7	13,8	4,1
7	3,4	2,2	2,7
8	2,6	3,2	2,5
9	2,5	1,8	2,1
10	4,6	8,5	5,9
11	6,0	5,2	5,4
12	5,6	3,1	2,8
13	2,5	2,1	1,9
14	4,5	13,8	3,8
15	4,1	1,6	1,8
16	1,8	8,1	1,8
17	3,7	4,6	2,7
18	6,0	10,1	6,2
19	4,8	6,1	3,3
20	4,2	1,5	2,8
21	4,4	8,4	3,3
22	4,5	10,5	4,8
23	6,1	4,8	5,2
24	8,6	10,7	7,3
25	9,6	15,6	9,7
26	7,9	8,0	6,8
27	10,4	26,3	11,1
28	9,8	10,2	8,8
29	6,4	3,7	5,3
30	5,2	7,5	3,6
Mean	4,8	6,9	4,2
Median	4,5	5,6	3,3
Std	2,4	5,4	2,5

Note: the Herfindahl index is defined as follows

$$100 * \sum_{i=1}^{207} x_i^2$$

where x_i is the bank's share in the i-th industrial/geographic segment

RESULTS TWO YEARS AFTER THE MERGER

TABLE A6: MAINTAINED OBLIGORS (TWO YEARS AFTER THE MERGER)

Merger identification number	Maintained obligors						
	as a % of total obligors at the time of the merger	% increase in exposure two years after	Expected default rate (%)	Expected default rate (weighted average) %		Expected loss (as a % of total exposure)	
				t	t+2	t	t+2
1	75,2	-6,1	1,01	0,74	0,68	0,22	0,18
2	74,2	0,6	0,87	0,65	0,63	0,19	0,19
3	80,7	19,8	1,22	1,11	1,01	0,76	0,69
4	77,4	19,2	1,07	0,90	0,84	0,39	0,36
5	76,2	17,6	1,52	1,71	1,48	0,69	0,60
6	70,4	12,3	0,98	0,94	0,78	0,38	0,32
7	81,6	18,0	1,14	1,06	0,98	0,42	0,39
9	77,1	-0,7	0,95	0,73	0,74	0,30	0,30
10	83,0	8,0	1,00	0,85	0,80	0,36	0,34
11	79,9	17,0	0,82	0,70	0,66	0,30	0,28
12	78,4	32,5	1,18	1,04	0,95	0,43	0,38
13	77,2	9,7	1,17	1,04	1,06	0,44	0,42
16	78,6	-3,5	1,15	0,85	0,86	0,41	0,43
17	79,1	18,9	0,91	0,81	0,74	0,34	0,31
18	81,2	21,7	0,85	0,90	0,84	0,39	0,36
20	77,5	-1,4	0,89	0,81	0,79	0,25	0,25
21	65,6	-8,1	0,82	0,80	0,78	0,33	0,32
23	81,5	18,3	1,12	1,12	1,05	0,38	0,38
25	73,0	26,6	1,32	1,23	1,23	0,49	0,48
27	86,9	15,3	0,82	0,81	0,81	0,43	0,41
28	79,7	23,6	0,69	0,72	0,65	0,20	0,19
29	72,1	1,7	0,90	0,84	0,79	0,28	0,28
Mean	**77,6**	**11,9**	**1,02**	**0,93**	**0,87**	**0,38**	**0,36**
Median	**78,0**	**16,1**	**0,99**	**0,85**	**0,81**	**0,38**	**0,35**

RESULTS TWO YEARS AFTER THE MERGER

TABLE A7: NEW AND DROPPED OBLIGORS TWO YEARS AFTER THE MERGER

Merger identification number	DROPPED BORROWERS					NEW BORROWERS				
	as a % of total obligors at the time of the merger	as a % of total exposure at the time of the merger	Expected default rate (%)	Expected default rate (weighted average) %	Expected loss (as a % of total exposure)	No. of new borrowers / no. of dismissed borrowers	Exposure to new borrowers as a % of total exposure two years after the merger	Expected default rate (%)	Expected default rate (weighted average) %	Expected loss (as a % of total exposure)
1	24,8	9,5	1,53	1,58	0,44	1,0	14,2	1,28	1,28	0,36
2	25,8	11,4	1,39	1,27	0,39	0,9	24,2	1,07	0,71	0,22
3	19,3	10,3	1,67	1,56	1,11	2,2	26,9	1,52	1,24	0,86
4	22,6	11,0	1,67	1,58	0,67	1,8	20,3	1,47	1,21	0,52
5	23,8	13,6	2,21	2,41	0,97	1,7	33,3	1,75	1,35	0,56
6	29,6	17,2	1,71	1,78	0,73	1,8	31,2	1,43	1,56	0,57
7	18,4	9,0	1,71	1,59	0,63	2,2	18,9	1,37	1,33	0,52
9	22,9	9,6	1,39	1,18	0,46	1,5	23,3	1,31	1,33	0,55
10	17,0	7,9	1,38	1,25	0,54	1,9	18,2	1,26	0,96	0,42
11	20,1	10,9	1,16	1,07	0,47	1,6	24,1	1,02	0,68	0,30
12	21,6	17,3	1,44	1,08	0,45	3,2	33,7	1,46	1,26	0,50
13	22,8	12,0	1,31	1,18	0,50	2,1	28,7	1,56	1,28	0,53
16	21,4	16,3	1,74	1,93	0,95	2,7	43,7	1,17	0,85	0,46
17	20,9	13,2	1,2	1,05	0,43	1,6	21,0	1,13	1,03	0,42
18	18,8	12,6	1,29	1,55	0,62	2,6	27,5	1,29	1,28	0,51
20	22,5	12,5	1,15	1,18	0,30	1,4	27,6	1,09	0,81	0,23
21	34,4	21,1	0,95	1,01	0,41	0,7	26,4	0,97	1,02	0,41
23	18,5	9,5	1,39	1,25	0,45	2,1	20,8	1,29	1,60	0,62
25	27,0	11,3	1,39	2,07	0,85	4,2	58,7	1,47	1,32	0,52
27	13,1	6,3	0,82	0,77	0,42	1,7	16,1	0,95	1,07	0,48
28	20,3	12,8	0,67	0,72	0,21	4,0	41,0	0,8	0,73	0,20
29	27,9	14,3	1,36	1,40	0,48	1,2	22,3	1,13	1,00	0,37
Mean	**22,4**	**12,3**	**1,39**	**1,38**	**0,57**	**2,0**	**27,4**	**1,26**	**1,13**	**0,46**
Median	**22,0**	**11,7**	**1,39**	**1,26**	**0,48**	**1,8**	**25,3**	**1,29**	**1,23**	**0,49**

RESULTS TWO YEARS AFTER THE MERGER
TABLE A7a: maintained vs. dropped borrowers

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: EXPECTED DEFAULT RATE
MAINTENED VS. DROPPED BORROWERS

Wilcoxon Scores (Rank Sums) for Variable edf
Classified by Variable TIPOC

TIPOC	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Mantenu	22	332	495	42,602817	15,09091
Persi	22	658	495	42,602817	29,90909

Wilcoxon Two-Sample Test

Statistic	332,0000
Normal Approximation Z	-3,8143
One-Sided Pr < Z	<.0001
Two-Sided Pr > !Z!	0,0001
t Approximation	
One-Sided Pr < Z	0,0002
Two-Sided Pr > !Z!	0,0004

Z includes a continuity correction of 0.5.

Median Scores (Number of Points Above Median) for Variable edf
Classified by Variable TIPOC

TIPOC	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Mantenu	22	5	11,0	1,677484	0,22727
Persi	22	17	11,0	1,677484	0,77273

Median Two-Sample Test

Statistic	5,0000
Z	-3,5768
One-Sided Pr < Z	0,0002
Two-Sided Pr > !Z!	0,0003

Van der Waerden Scores (Normal) for Variable edf
Classified by Variable TIPOC

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Mantenu	22	-10,928	0	3,107066	-0,49674
Persi	22	10,9283	0	3,107066	-0,49674

Van der Waerden Two-Sample Test

Statistic	-10,9283
Z	-3,5172
One-Sided Pr < Z	0,0002
Two-Sided Pr > !Z!	0,0004

Savage Scores (Exponential) for Variable edf
Classified by Variable TIPOC

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Mantenu	22	-11,528812	0	3,183898	-0,524
Persi	22	11,528812	0	3,183898	0,52404

Savage Two-Sample Test

Statistic	-11,5288
Z	-3,621
One-Sided Pr < Z	0,0001
Two-Sided Pr > !Z!	0,0003

RESULTS TWO YEARS AFTER THE MERGER
TABLE A7b: new vs. dropped borrowers

NONPARAMETRIC TESTS ON THE EQUALITY OF MEDIANS
VARIABLE: EXPECTED DEFAULT RATE
NEW VS. DROPPED BORROWERS

Wilcoxon Scores (Rank Sums) for Variable edf
Classified by Variable TIPOC

TIPOC	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Nuovi	22	433	495	42,60282	19,68182
Persi	22	557	495	42,60282	25,31818

Wilcoxon Two-Sample Test

Statistic	433,0000
Normal Approximation Z	-1,4436
One-Sided Pr < Z	0,0744
Two-Sided Pr > !Z!	0,1489
t Approximation	
One-Sided Pr < Z	0,0781
Two-Sided Pr > !Z!	0,1561

Z includes a continuity correction of 0.5.

Van der Waerden Scores (Normal) for Variable edf
Classified by Variable TIPOC

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Nuovi	22	-4,0873	0	3,107066	-0,18579
Persi	22	4,08729	0	3,107066	0,185786

Van der Waerden Two-Sample Test

Statistic	-4,0873
Z	-1,3155
One-Sided Pr < Z	0,0942
Two-Sided Pr > !Z!	0,1883

Median Scores (Number of Points Above Median) for Variable edf
Classified by Variable TIPOC

TIPOC	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Nuovi	22	8,0	11,0	1,677484	0,36636
Persi	22	14,0	11,0	1,677484	0,63636

Median Two-Sample Test

Statistic	8,0000
Z	-1,7884
One-Sided Pr < Z	0,0690
Two-Sided Pr > !Z!	0,0737

Savage Scores (Exponential) for Variable edf
Classified by Variable TIPOC

TIPOB	N	Sum of Scores	Expected Under H0	Std Dev Under H0	Mean Score
Nuovi	22	-4,796143	0	3,183898	-0,218
Persi	22	4,796143	0	3,183898	0,21801

Savage Two-Sample Test

Statistic	-4,7961
Z	-1,5064
One-Sided Pr < Z	0,0660
Two-Sided Pr > !Z!	0,1320

RESULTS TWO YEARS AFTER THE MERGER

TABLE A8: EXPECTED DEFAULT RATE AND EXPECTED LOSS

Merger identification number	Expected default rate		Expected default rate (weighted average)		Expected loss (*)	
	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years
1	1,14%	1,08%	0,82%	0,77%	0,24%	0,20%
2	1,01%	0,92%	0,72%	0,65%	0,22%	0,20%
3	1,31%	1,33%	1,16%	1,08%	0,80%	0,73%
4	1,20%	1,21%	0,98%	0,91%	0,42%	0,40%
5	1,69%	1,60%	1,80%	1,44%	0,73%	0,59%
6	1,19%	1,18%	1,08%	1,02%	0,44%	0,40%
7	1,25%	1,22%	1,11%	1,04%	0,44%	0,41%
9	1,05%	1,06%	0,77%	0,88%	0,32%	0,36%
10	1,07%	1,08%	0,88%	0,83%	0,37%	0,35%
11	0,89%	0,88%	0,74%	0,67%	0,32%	0,29%
12	1,24%	1,31%	1,05%	1,06%	0,43%	0,42%
13	1,20%	1,32%	1,05%	1,12%	0,45%	0,45%
16	1,28%	1,16%	1,03%	0,86%	0,50%	0,45%
17	0,97%	0,98%	0,84%	0,80%	0,35%	0,33%
18	0,93%	1,01%	0,98%	0,96%	0,42%	0,40%
20	0,95%	0,95%	0,86%	0,80%	0,26%	0,25%
21	0,87%	0,86%	0,85%	0,84%	0,35%	0,34%
23	1,17%	1,17%	1,14%	1,17%	0,38%	0,43%
25	1,34%	1,41%	1,32%	1,28%	0,53%	0,50%
27	0,82%	0,85%	0,81%	0,85%	0,43%	0,42%
28	0,68%	0,75%	0,72%	0,68%	0,20%	0,19%
29	1,03%	0,98%	0,92%	0,84%	0,31%	0,30%
MEAN	1,10%	1,10%	0,98%	0,93%	0,40%	0,38%
MEDIAN	1,10%	1,08%	0,95%	0,87%	0,40%	0,40%
STD	0,22%	0,21%	0,24%	0,20%	0,15%	0,13%

(*) as a percentage of portfolio exposure (EAD)

RESULTS TWO YEARS AFTER THE MERGER

TABLE A9: UNEXPECTED LOSS, CONCENTRATION RISK, SYSTEMATIC RISK

Merger identification number	Unexpected loss (*)		Concentration risk (*)		Systematic risk (*)	
	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years	Merged bank	Merged bank after 2 years
1	3,45%	1,83%	3,38%	1,77%	0,07%	0,07%
2	1,58%	2,07%	1,38%	1,97%	0,20%	0,10%
3	2,67%	2,80%	1,14%	1,54%	1,53%	1,26%
4	1,58%	1,59%	1,19%	1,23%	0,39%	0,36%
5	1,67%	1,83%	0,98%	1,51%	0,69%	0,32%
6	1,79%	1,66%	1,21%	1,12%	0,58%	0,55%
7	1,33%	1,35%	1,01%	0,90%	0,32%	0,45%
9	1,29%	1,19%	0,91%	0,73%	0,39%	0,46%
10	1,26%	1,18%	0,80%	0,68%	0,46%	0,50%
11	1,13%	1,31%	0,59%	1,12%	0,54%	0,19%
12	1,70%	2,71%	0,87%	2,39%	0,83%	0,32%
13	1,95%	1,51%	1,88%	0,68%	0,08%	0,82%
16	1,84%	3,01%	1,15%	2,79%	0,69%	0,22%
17	1,43%	1,39%	0,49%	0,93%	0,94%	0,46%
18	1,83%	1,70%	0,53%	0,55%	1,30%	1,15%
20	0,96%	1,47%	0,61%	1,34%	0,35%	0,13%
21	2,38%	2,78%	1,98%	2,50%	0,41%	0,28%
23	1,61%	1,83%	0,70%	0,66%	0,90%	1,16%
25	4,02%	2,87%	3,38%	1,53%	0,64%	1,34%
27	2,83%	2,94%	1,61%	2,01%	1,22%	0,93%
28	1,67%	1,35%	0,94%	0,73%	0,73%	0,62%
29	1,61%	1,77%	0,74%	1,06%	0,87%	0,71%
MEAN	1,89%	1,92%	1,25%	1,35%	0,64%	0,56%
MEDIAN	1,67%	1,74%	1,00%	1,18%	0,61%	0,46%
STD	0,75%	0,63%	0,80%	0,65%	0,38%	0,39%

(*) as a percentage of portfolio exposure (EAD)

RESULTS TWO YEARS AFTER THE MERGER
TABLE A9a: Statistical tests

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: UNEXPECTED LOSS
merged banks at the time of the deal vs. two years after

Variable: diftempo

N	22	Sum Weights	22
Mean	-0,0002644	Sum Observations	-0,0058179
Std Deviation	0,00597373	Variance	0,00003569
Skewness	0,86198332	Kurtosis	2,52787192
Uncorrected SS	0,00075093	Corrected SS	0,00074939
Coeff Variation	-2258,9263	Std Error Mean	0,0012736

Basic Statistical Measures

Location		**Variability**	
Mean	-0,00026	Std Deviation	0,00597
Median	-0,000660	Variance	0,0000357
Mode	.	Range	0,02785
		Interquartile Range	0,00349

Tests for Location: Mu0=0

Test		**Statistic**	**p Value**	
Student's t	t	-0,20764	Pr > !t!	0,8375
Sign	M	-2	Pr >= !M!	0,5235
Signed Rank	S	-27,5	Pr >= !S!	0,3843

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: CONCENTRATION RISK
merged banks at the time of the deal vs. two years after

Variable: diftempo

N	22	Sum Weights	22
Mean	-0,0010441	Sum Observations	-0,02297
Std Deviation	0,0083623	Variance	6,993E-05
Skewness	0,6911409	Kurtosis	1,2128707
Uncorrected SS	0,0014925	Corrected SS	0,0014685
Coeff Variation	-800,91085	Std Error Mean	0,0017829

Basic Statistical Measures

Location		**Variability**	
Mean	-0,00104	Std Deviation	0,00836
Median	-0,00186	Variance	0,0000699
Mode	.	Range	0,03492
		Interquartile Range	0,0065

Tests for Location: Mu0=0

Test		**Statistic**	**p Value**	
Student's t	t	-0,58564	Pr > !t!	0,5644
Sign	M	-2	Pr >= !M!	0,5235
Signed Rank	S	-34,5	Pr >= !S!	0,2725

PARAMETRIC AND NONPARAMETRIC TESTS FOR PAIRED SAMPLES
VARIABLE: SYSTEMATIC RISK
merged banks at the time of the deal vs. two years after

Variable: diftempo

N	22	Sum Weights	22
Mean	0,00077965	Sum Observations	0,01715228
Std Deviation	0,00328938	Variance	0,00001082
Skewness	-1,2164969	Kurtosis	1,68800431
Uncorrected SS	0,00024059	Corrected SS	0,00022722
Coeff Variation	421,905243	Std Error Mean	0,0007013

Basic Statistical Measures

Location		**Variability**	
Mean	0,00078	Std Deviation	0,00329
Median	0,001186	Variance	0,0000108
Mode	.	Range	0,01254
		Interquartile Range	0,00325

Tests for Location: Mu0=0

Test		**Statistic**	**p Value**	
Student's t	t	1,111723	Pr > !t!	0,2788
Sign	M	5	Pr >= !M!	0,0525
Signed Rank	S	52,5	Pr >= !S!	0,0883

RESULTS TWO YEARS AFTER THE MERGER

TABLE A10: DIVERSIFICATION BY INDUSTRIAL/GEOGRAPHIC SEGMENT

Merger identification number	Herfindahl index	
	Merged bank	Merged bank after 2 years
1	2,7	2,4
2	2,1	2,2
3	2,0	1,7
4	1,5	1,6
5	2,2	2,4
6	4,1	3,6
7	2,7	2,5
9	2,1	2,0
10	5,9	5,3
11	5,4	4,5
12	2,8	2,5
13	1,9	1,6
16	1,8	1,8
17	2,7	2,6
18	6,2	5,4
20	2,8	2,6
21	3,3	4,3
23	5,2	5,1
25	9,7	8,4
27	11,1	10,5
28	8,8	7,4
29	5,3	5,1
Mean	4,2	3,9
Median	2,8	2,6
Std	2,7	2,4

Note: the Herfindahl index is defined as follows

$$100 * \sum_{i=1}^{207} x_i^2$$

where x_i is the bank's share in the i-th industrial/geographic segment