# Utilizing Artificial Neural Network Model to Predict Bank Stock Returns

by

***Vincenzo Pacelli*** [*]
*Dottore di Ricerca – Università degli Studi "La Sapienza" di Roma*

## Abstract

The objective of this paper is to propose a non-linear mathematical model, represented by an artificial neural network, to analyze the dynamics of stock prices of banks. The research is based on the idea that, about the shareholders' value added in banking, the comparison of linear methods of analysis and non-linear ones is able to discover aspects of the phenomenon otherwise invisible.
Through the empirical application of the artificial neural network developed and through the comparison with the linear correlation analysis, it is expected to obtain some indications about the phenomena and variables that can influence banks' stock returns, particularly on their quantitative or qualitative nature and on their level of disclosure. The research also aims to provide empirical results about the use of non-linear methods of analysis for the study of the dynamics of banks' stock prices, enriching the prospects for research in terms of methodological tools.
This paper intends to contribute to the literature on the methodological tools used for the analysis of the efficiency of capital markets in the field of forecasting and interpreting the dynamics of stock prices of listed companies, with a specific focus on banking.

***JEL Classification: C3, C32, C45, C5, C63, G12, G14, G15, G21.***

***Keywords: Neural Networks; Forecasting; Stock Returns; Banks.***

## Contents

1. Introduction and research hypothesis
2. Literature review
3. The method: the artificial neural network model
4. Description of the data
5. The empirical results
    5.1. Empirical results based on the correlation analysis
    5.2. Empirical results based on the neural network model
6. Concluding remarks
Appendix
References

[*] Please send all correspondence to e-mail address: vincenzopacelli@libero.it

## 1. Introduction and research hypothesis

The initial hypothesis on which this research is based is that different forms of capital contribute to the creation of the value and the price of the economic capital of a bank. These forms of capital, through their interacting and integrating in the banking production processes, are able to determine the competitive advantage and the reputation of a bank in the market.

> **H1:** *Different forms of capital contribute to the creation of the value and the price of the economic capital of a bank.*

This hypothesis follows freely the wake of Fisher (1892), according to which all flows of income and value can be designed as interest originated by a capital in its tangible or intangible components. The underlying assumption of this hypothesis, however, requires a prior, absolutely impossible to elude definition of the capital in firms, in general, and in banks, in particular.

This research interprets as integral parts of the capital of a bank all those corporate resources which: *(a)* present a patrimonial content, on which the bank exercises an actual and an exclusive power to control and management within a period of time; *(b)* are able to generate income, both independently from the rest of the assets of the bank and in combination with some – or all – other factors of production, and provided that their contribution is actually relevant for the production of income.

The capital of a bank can therefore be considered as a manifold aggregate of factors of production, characterized by different nature and features, which can contribute to the process of producing income of the bank. So, varying the taxonomic criteria, the capital of a bank can take different forms, in other words characterized by different nature and features.

In order to develop the artificial neural network model, in this paper the taxonomy of forms of capital in banks is regarded as follows:

- financial capital, or:
  - equity;
  - tier 1 and total capital;
- tangible capital, and different from financial resources;
- intangible capital, which – unlike the previous two forms of capital – has also an invisible nature because not exhaustively noted in the Balance Sheet and because without a material consistency that makes this form of capital difficult to identify.

The high level of integration between the different forms of capital of a bank causes considerable difficulties in accounting and measuring the contribution offered by each form of capital to the processes of creation and diffusion of economic value. These difficulties determine, for both the bank and its stakeholders, relevant prejudices that can be distinguished in:

- internal prejudices of the bank, or: *(a)* inefficiency in the management and control of the corporate capital; *(b)* risk of insider trading and opportunistic behaviour of the management; *(c)* high agency costs for shareholders
- external prejudices, or: *(d)* continuous and significant imbalance between the prices at which shares are traded in the Stock Exchange and the accounting data which

should reflect the present and the future economic performance of quoted banks; *(e)* volatility and uncertainty in financial markets; *(f)* informative inefficiency to the prejudice of the bank's shareholders and stakeholders; *(g)* risk of discrimination of some banks (typically those intangible-intensive).

As pointed out so far highlights the importance of the issue of measuring the contribution offered by the different forms of capital of a bank to the creation of the value and price of the economic capital in banks. So far the scientific literature, as thoroughly discussed in the next paragraph, has addressed the analysis of the relations that bind the dynamics of the company's capital with stock returns of its shares primarily through linear methods of analysis. Furthermore, in most of the studies conducted the banks are excluded from the analysis. This leads to obvious gaps in financial literature, both about the empirical deepening of the relations between some forms of capital (intangible capital) and value in the banking industry, and about the analysis of the methodological tools used to study the phenomena analyzed.

As underlined let me introduce the second and third research hypothesis which are closely linked to the previous one.

> **H2:** *There are intangibles that influence bank stock returns but that are not measurable or accountable through linear methods of analysis that consider only quantitative and public data.*
>
> **H3:** *About the shareholders' value added in banking, the comparison of linear methods of analysis and non-linear ones is able to discover aspects of the phenomenon otherwise invisible.*

The third research hypothesis proposed, which is essentially methodological, is led by the two previous ones and introduces the central subject of theoretical and empirical study in this research. The paper has in fact a dual objective: *(a)* to analyze empirically the dynamics of capital and value in a panel of listed banks through the comparison of linear methods of analysis and non-linear ones; *(b)* to propose a non-linear mathematical model, represented by an artificial neural network, to analyze the dynamics of stock prices of banks.

## 2. Literature review

This paper aims to contribute to the literature on the methodological tools used for the analysis of the efficiency of capital markets [*Fama (1970); Grossman (1976); Grossman, Stiglitz (1980); Tobin (1984); White (1988); Clemen (1989); Granger, Newbold (1989); Fama, French (1993); Grudnitski, Osburn (1993); Clements, Hendry (1998); Makridakis, Wheelwright, Hyndman (1998); Gabbi (1999); Shachmurove, Witkowoska (2000)*] in the field of forecasting and interpreting the dynamics of stock prices of listed companies, with a specific focus on the utilizing of artificial neural networks to the prediction of stock prices of banks, that is an issue still unexplored by literature.

In the last twenty years there has been a growing body of literature based on the comparison of artificial neural network to traditional statistical methods of analysis.

Hertz, Krogh and Palmer (1991) offer a comprehensive view of neural networks and issues of their comparison to statistics.

Many economists also advocate the application of neural networks to different fields in economics and finance [*Altman, Marco, Varetto (1994); Baestaens (1994); Bierens (1994); Buscema, Sacco, Matera, Nocentini (1997); Cheh, Weinberg, Yook (1999); Cogger, Koch, Lander (1997); Cooper (1999); Dolcino, Giannini, Rossi (1998); Gabbi (1999); Gallant, White (1988a); Gallant, White (1988b); Gargantini (2003); Grudnitski, Osburn (1993); Hamm, Brorsen B. Wade (2000); Hawley, Johnson, Raina (1990); Hu, Tsoukalas (1999); Jagielska (1993); Kuan Chung-Ming (1989); Kuan Chung-Ming, Hornik, White (1990); Kuan Chung-Ming, White (1991); Kuan Chung-Ming, White (1994); Ling (1993); Marco, Varetto (1994); Maspero, Rossignoli (2000); McNelis (2004); Potscher, Prucha (1991a); Potscher, Prucha (1991b); Refenes (1995); Refenes, White (1998); Shachmurove, Witkowoska (2000); Trippi, Turban (1996); Wang, Chan (1993); White (1988); White (1992); Windsor, Harker (1990); Witkowska (1995)*].

The non-linear and often obscure relations that govern the economic and financial variables, the presence of significant amounts of data and the failures of the conventional mathematical and statistical models have encouraged a growing development of studies on the neural networks in the economic and financial fields. Many studies were devoted in particular to the study of neural networks as models able to predict historical time series of economic and financial data [*Clemen (1989); Clements, Hendry (1998); Gabbi (1999); Granger (1980); Granger (1989); Granger, Newbold (1989); Granger, Ramanathan (1984); Makridakis, Wheelwright, Hyndman (1998); White (1988); White (1992)*]. According to Granger (1991) non-linear relationships in financial and economic data are more likely to occur than linear relationships. Several authors have also examined the application of neural networks to financial markets, where the non-linear properties of financial data provide many difficulties for traditional methods of analysis [*Omerod, Taylor, Walker (1991); Grudnitski, Osburn (1993); Altman, Marco, Varetto (1994); Kaastra, Boyd (1995); Witkowska (1995)*].

About the specific theme of this research, Yoon and Swales (1997) compare neural networks to discriminative analysis with respect to the prediction of stock price performance and find that the neural network is superior to discriminative analysis in its predictions. So neural networks can be designed and trained to discern historical data patterns in order to predict future stock price trends.

Kryzanowski, Galler and Wright (1993) and Zirilli (1997) have shown that neural networks can recognize stocks outperforming the market. Kryzanowski, Galler and Wright (1993) also trained neural networks to classify correctly 72% of the test stocks in relation to their performance. Refenes (1995) and Bansal and Viswanathan (1993) explore a dynamic version of the arbitrage pricing model (APT), replacing linear regression with neural networks to rank stocks. These authors find that, compared to regression models, neural networks better identify stocks that outperform the market.

As we can see from this literature review, there are some studies which have been focused on the application of neural networks to the prediction of stock price performance of listed companies. In this studies, however, banks are often excluded from the analysis. The available literature on relations between corporate variables and stock prices of banks uses in fact linear methods of analysis [*Cooper, Jackson, Patterson (2003); Romagnoli (2007)*]. So there is not a specific literature on the empirical application of neural networks to forecast the stock prices of banks. Hence this research aims to contribute to cover this gap in the literature.

## 3. The method: the artificial neural network model

As regards the method this research is based on the hypothesis that, about the shareholders' value added in banking, the comparison of linear methods of analysis and non-linear ones is able to discover aspects of the phenomenon otherwise invisible.
An empirical analysis was then carried out jointly using a linear method of analysis (such as the General Correlation Model – $GC_m$)[1] and non-linear one (such as an Artificial Neural Network Model – $ANN_m$).
Artificial Neural Networks are non-linear mathematical models that can be trained to map past and future values of time series data and thereby extract hidden relationship that govern the data. Artificial Neural Networks consist of multiple neurons which are extensively interconnected and organized in layers similar to those of a decision tree. These neurons work in unison to solve specific problems and, when trained through time series of data, become potent tools for analysis and forecasting.
A single artificial neuron, which is the basic element of the neural network, comprises several inputs ($i_1, i_2, \ldots, i_m$) and one output (y) that can be written as follows:

$$(2) \qquad y = f(i_n, w_n)$$

where, $w_n$ are the function parameter weights of the function f.
Equation (2) is called an activation function. Each artificial neuron determines its output by applying an activation function and weights to inputs. The activation function of the $ANN_m$ developed for this research is the symmetrical sigmoid function that can be written as follows:

$$(3) \qquad f(y) = 1 / [1 + \exp(-k\Psi y)]$$

where, $\Psi > 0$ is the slope of sigmoid in its point of inflection y = 0, and k is a constant. The output (y) of the symmetrical sigmoid function is included in the range [-1, 1].
With regard to architecture of the $ANN_m$, it has developed a neural network multilayer fully connected[2] and characterized by 4 hidden layers[3]. The neurons in each layer are: 27 input neurons, 15 neurons in the first hidden layer, 10 neurons in the second hidden layer, 10

[1] The equation for calculating the correlation coefficient (General Correlation Model – $GC_m$) is the follow:

$$(1) \qquad \text{Correl}(X, Y) = \sum(x_m - x)(y_m - y)/[\sqrt{\sum(x_m - x)^2 \sum(y_m - y)^2}]$$

where, $x_m$ e $y_m$ are the average values of data of the panel analyzed.
[2] This means that, if any neuron within a layer is connected to a neuron of the next layer, then all the neurons of the first layer will be connected to neurons of the second layer, and so for the various layers of the $ANN_m$.
[3] To carry out the neural networks used in this research it has been used the library FANN (Fast Artificial Neural Network Library), which is public and freely available and which is a provider of architecture for the realization of artificial neural networks. The library FANN provides users with different software available to implement neural networks useful for different purposes of research or analysis. Obviously the theoretical development, the implementation and the training of the $ANN_m$ are responsibilities of users of the software.

neurons in the third hidden layer, 7 neurons in the fourth hidden layer and 1 output neuron (Figure 1).

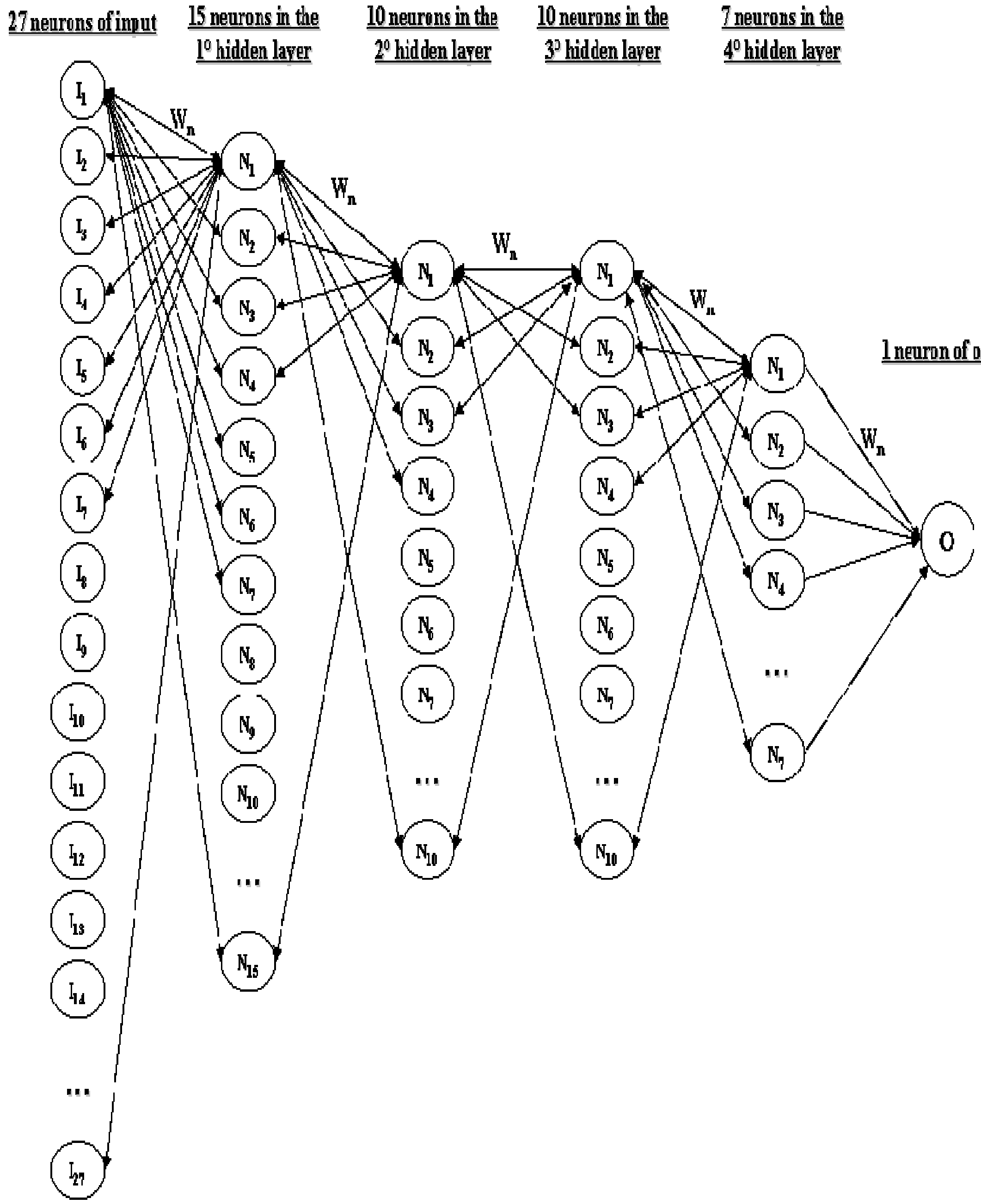


**Figure 1: Architecture of the ANN$_m$**

The response of an artificial neural network is determined by the synaptic values (weights) of the connections between the nodes of the neurons. In the same way biological nervous systems are able of learning by experience, artificial neural networks learn the reality analyzed by changing gradually their synaptic values (weights) $\Delta W_{ij}$ when trained through time series of data (pattern of input and output) and through the use of a learning algorithm. The learning algorithm used in the training of the $ANN_m$ developed is the back propagation algorithm with learning for cycles (on line). It is so developed an $ANN_m$ feed-forward. In the learning for cycles, the changing of the synaptic values (weights) $\Delta W_{ij}$ of the $ANN_m$ is calculated after each presentation of a single pattern. The new configuration of the synaptic values (weights) after a cycle of training is calculated by adding the change obtained $\Delta W_{ij}(t)$ to the previous configuration of the synaptic values $W_{ij}(t-1)$. The speed of learning is regulated by a constant η – the learning rate – which defines the portion of change that is applied to the synaptic values. The equation of learning can be write as follows:

$$(4) \qquad W_{ij}(t) = W_{ij}(t-1) + \eta\, \Delta W_{ij}(t),$$

where, $0< \eta<1$ and, in the $ANN_m$ developed, $\eta = 0{,}7$.
The training of the $ANN_m$ developed was interrupted when the mean square error has become less of the value 0,0001. At the end of the training of the first $ANN_m$ (output at time "t") the mean square error was 0,00002. At the end of the training of the second $ANN_m$ (output at time "t+1") the mean square error was 0,00007.
Once the learning phase was completed, the synaptic values are frozen and it is possible to study the response of the $ANN_m$ on other patterns of data in the phase of test. The phase of test consists in the presentation of new patterns and in the calculation of activation of the nodes of the $ANN_m$ with synaptic weights frozen.
It was carried out testing of the $ANN_m$ through three patterns of input and output (records) that have not been used for the training. The results of the tests of the 2 $ANN_m$ were as follows: *(a)* the mean square error for the first $ANN_m$ (output at time "t") was 0,0031; *(b)* the mean square error for the second $ANN_m$ (output at time "t +1") was 0,0465. So both the $ANN_m$ are very precise. This means that the $ANN_m$ developed have a good ability to generalization and interpretation of the phenomenon analyzed[4].

## 4. Description of the data

In order to train and test the $ANN_m$ developed, an empirical study was conducted on the dynamics of capital and the ability to create and diffuse economic value by a panel of listed European banks (see Appendix B).
The empirical analysis was conducted from 2002 to 2006 on the banks listed in Table 1.
The panel of banks was selected from a population of European banks listed, active and independent at the end of December 2006[5].

[4] The ability of generalization of a neural network is about the ability to produce an appropriate response to a pattern of input that was not included in the training phase. The only problem may be represented by a possible overfitting of the neural networks that would decrease the probability that neural networks discover the general function that describes the phenomenon analyzed. This problem can be overcome by increasing the number of the pattern of input and output used for the training and the testing of the neural networks.
[5] The empirical analysis was conducted on data from consolidated balance of banks by source Bankscope.

| Banks |
| --- |
| ABN Amro (Netherlands)<br>Banca Carige S.p.A. (Italy)<br>Banca Intesa S.p.A. - Intesa Sanpaolo (Italy)<br>Banca Lombarda e Piemontese S.p.A. (Italy)<br>Banco Bilbao Vizcaya Argentaria SA (Spain)<br>Banco Santander Central Hispano (Spain)<br>BNP Paribas (France)<br>Capitalia S.p.A. (Italy)<br>Cassa di Risparmio di Firenze S.p.A. (Italy)<br>Commerzbank AG (Germany)<br>Credito Emiliano S.p.A. (Italy)<br>Deutsche Bank AG (Germany)<br>Mediobanca S.p.A. (Italy)<br>Monte dei Paschi di Siena S.p.A. (Italy)<br>Société Générale (France)<br>UniCredit S.p.A. (Italy) |

**Table 1: Banks analyzed**

Using data emerged from the empirical analysis, 2 different $ANN_m$ have developed which are completely identical in both mathematical and scientific architecture and about the inputs used, but which are different about the output considered. The first $ANN_m$ considers as output the per cent annual variation of the share prices of banks in the reference year of the inputs (year "t"). The second $ANN_m$ considers as output the per cent annual variation of the share prices of banks in the year following that reference the inputs (year "t+1").
The 27 inputs used in the 2 $ANN_m$ were calculated for the 16 banks investigated and for the 3 years analyzed (48 patterns of input and output or 48 records). The 27 inputs are as follows:

- Net income;
- per cent annual variation of the Total Capital;
- per cent annual variation of the Equity;
- per cent annual variation of the Total Capital ratio;
- per cent annual variation of the Tier 1 Capital ratio;
- per cent annual variation of the Capital Funds to Liabilities ratio;
- per cent annual variation of the Total Assets;
- per cent annual variation of the Total Earning Assets;
- per cent annual variation of the Fixed Assets;
- per cent annual variation of the Intangible Assets by bank's accounting;
- per cent annual variation of the Cost to Income ratio;
- per cent annual variation of the Net Interest Margin ratio, which can be estimated as follows:

(5) Net Interest Margin = (Interest Margin/Average Total Earning Assets)*100

- Knowledge Capital Earning (KCE), which can represent an indicator about the variation of the organizational capital[6] and can be estimated as follows:

(6) KCE = (Net Interest Margin - Tasso EURIBOR)*Total Earning Assets

- per cent annual variation of the Deposits & Short Term Funding;
- per cent annual variation of an evaluation of Brand towards customers, which can be estimated as follows:

(7) $\Delta V_b$ = ($\Delta$ bank "x" funding) - ($\Delta$ banks analyzed average funding)

- per cent annual variation of the Dividend Pay Out ratio;
- per cent annual variation of the Price to Book Value ratio;
- per cent annual variation of the Price to Earning ratio;
- per cent annual variation of an evaluation of the reputational (or relational) capital (RCV) towards financial markets, which can be estimated as follows:

(8) RCV = [(P/BV) - (Roae/Ke)]*Equity

- per cent annual variation of the Return on Average Equity ratio;
- per cent annual variation of the cost of equity ($K_e$) which can be estimated by using the Capital Asset Pricing Model as follows:

(9) $K_e = r_f + \beta(r_m - r_f)$

where:
  - $r_f$ is the riskless return rate and was estimated as equal to the annual average of the Euribor rate at 3 months;
  - $r_m$ is the expected market return rate for similar investments and was estimated as equal to 9,16% which is the minimum annual return rate – between 2002 and 2006 – of the Italian banking sector index by Borsa Italiana;
  - $\beta$ is the beta of the share and expresses the historical relation between the variation of market returns and the variation of the share returns. In other words, the beta of the share measures the sensitivity of the share trend to the variations of the market index. The beta of a one-year share has been considered as correlated with the Mib 30 Index (for Italian banks) and with the DJ Euro Stoxx 50 index (for Foreign banks).

- per cent annual variation of the economic capital value, which was estimated by using a revenue method as follows:

[6] See Lev (2001); Aiaf (2003), pp. 40-41.

(10) Economic Capital Value = Net Income/ $K_e$

- per cent annual variation of the annual average of the Euribor rate at 3 months;
- per cent annual variation of the Beta;
- annual Volatility of shares prices, which was estimated as follows:

(11) $V_p = [(P_{Max} - P_{Min})/( P_{Dec})]*100$

where:

  - $P_{Max}$ is the high annual value of the share prices;
  - $P_{Min}$ is the low annual value of the share prices;
  - $P_{Dec}$ is the share price at December of the year analyzed.

- per cent variation – between 2 year – of the Net income;
- upgrade or downgrade of Fitch Rating Long Term.

The inputs' portfolio developed provides – as a whole – an estimate of the dynamics of the variables which determine the supply and demand of the economic capital of a bank. The $ANN_m$ developed, therefore, aims to enhance the impact of each variable of input considered on the bank share prices (output of the $ANN_m$).
Once developed and tested the 2 $ANN_m$, in order to determine the effects on outputs caused by the variations of each input, it is proceeded – for the 2 $ANN_m$ – as follows.
Increased individually by 10% the values of each input of the 2 $ANN_m$, keeping time to time constant the values of the other 26 input, it was studied the deviations of the output produced by the $ANN_m$ as a result of the variation of the input from the output expected, namely that provided by the $ANN_m$ without variations of inputs.

(12) First $ANN_m$: $O_t = f[(1,10 * I_1); K\ I_{2\text{-}27}]$

(13) Second $ANN_m$: $O_{t+1} = f[(1,10 * I_1); K\ I_{2\text{-}27}]$

In order to be used to train the $ANN_m$, the patterns of input and output must be appropriately amended (normalised) through their transformation into the range [-1, 1] as follows:

(14) $I = I_{min} + [(I_{max}-I_{min})*(D-D_{min})/(D_{max}-D_{min})]$

where:

- $D_{min}$ and $D_{max}$ are the extreme values of the ranges – namely the maximum and minimum values – of the variables of input and output;
- $D$ is the value of each input and output;
- $I_{max}$ and $I_{min}$ are the new extreme values of the range or "-1" and "1".

## 5. The empirical results

### *5.1. Empirical results based on the correlation analysis*

This paragraph introduces the results of a linear correlation analysis conducted – for the panel of banks and for the period analyzed – including some measures of risk of the bank's management and the ability of banks to create economic value (Table 2) and to diffuse economic value in share prices (Table 3). In other words, the analysis shows the correlation coefficients that bind the annual performances in terms of economic value created for the shareholders and the annual stock returns of the banks with some measures of risk of the bank's management, where the risk of the bank's management can be generally identified with the variability of possible values of some indicators around a mean expected value (see Appendix B)[7].

| **Correlation coefficients** | **(Roae - $K_e$)** | | | |
|---|---|---|---|---|
| | *2003* | *2004* | *2005* | ***Average*** |
| **Δ % $K_e$** | -0,700 | -0,200 | -0,353 | ***-0,418*** |
| **Δ % Beta** | -0,336 | -0,280 | -0,032 | ***-0,216*** |
| **Δ % Total Capital** | 0,337 | 0,017 | -0,297 | ***0,019*** |
| **Δ % Total Capital Ratio** | -0,024 | 0,088 | 0,357 | ***0,140*** |
| **Δ % Net Income** | 0,665 | -0,493 | -0,181 | ***-0,003*** |
| **Δ Fitch Rating Long Term** | -0,285 | n.d. | 0,183 | ***-0,051*** |
| **Volatility % Market Price** | -0,627 | -0,344 | -0,443 | ***-0,471*** |

**Table 2: Correlation coefficients between risk and value (1/2) (See Appendix B)**

[7] It was then estimated the risk of the bank's management through the annual variation of the following variables:

- per cent annual variation of the cost of equity ($K_e$) which was estimated by using the Capital Asset Pricing Model described in paragraph 4;
- per cent annual variation of the Beta;
- per cent annual variation of the Total Capital;
- per cent annual variation of the Total Capital ratio;
- per cent variation – between 2 year – of the Net income;
- upgrade or downgrade of Fitch Rating Long Term;
- annual Volatility of shares prices;
- per cent annual variation of the economic value which was estimated as difference between the Roae and the $K_e$.

See paragraph 4.

| Correlation coefficients | Δ % Market Price | | | |
|---|---|---|---|---|
| | *2002-2003* | *2003-2004* | *2004-2005* | ***Average*** |
| **Δ % $K_e$** | 0,339 | 0,408 | -0,287 | ***0,153*** |
| **Δ % Beta** | 0,171 | 0,308 | -0,358 | ***0,040*** |
| **Δ % Total Capital** | -0,291 | -0,102 | 0,022 | ***-0,124*** |
| **Δ % Total Capital Ratio** | 0,208 | 0,234 | -0,183 | ***0,086*** |
| **Δ % Net Income** | -0,334 | 0,722 | 0,633 | ***0,340*** |
| **Δ Fitch Rating Long Term** | 0,100 | n.d. | 0,089 | ***0,095*** |
| **Volatility % Market Price** | 0,879 | 0,609 | 0,933 | ***0,807*** |
| **Roae - $K_e$** | -0,732 | -0,124 | -0,475 | ***-0,444*** |

**Table 3: Correlation coefficients between risk and value (2/2) (See Appendix B)**

The analysis of the data reveals the following relevant aspects:

- a significant positive correlation emerges between the banks' capacity to create economic value in the reference year and their annual Price to Book Value ratio (P/BV). In other words, the best performances in terms of creating economic value are pursued by the banks from which the market expects a high future growth value;
- an average significant correlation does not emerge between the bank stock returns and the variations of the total capital and the capital adequacy to risk weighted assets of the banks. This emerges also about the ability of the banks to create economic value. An increase in the level of risk of banking for its shareholders and stakeholders, represented by a reduction in the level of total capital or capital adequacy to the risks assumed by the bank, does not seem so far to influence both the bank stock returns and the performances of the banks in terms of economic value created;
- an average significant correlation does not emerge between the banks stock returns and the variations of the $K_e$ and beta of the banks which respectively express an estimate of the variation in the level of the bank's risk as perceived by its shareholders and a measure of the sensitivity of the share trend to the variations of the market index. Obviously a negative significant correlation emerges between the performances of the banks in terms of economic value created and their variations of the $K_e$ and beta. An increase in the level of the risk perceived by the market rises in fact the $K_e$ and, as a result, the threshold of profitability to be achieved in order to create economic value for the shareholders;
- discrepant data emerge with reference to the correlation between the banks stock returns and their economic performances. On the one hand, especially in 2004, a positive significant correlation emerges between the per cent variation – between 2 year – of the net income and the banks stock returns in the second year. On the other hand, instead, a negative significant correlation emerges between the annual banks' capacity to create economic value and their stock returns;
- an average significant correlation does not emerge between the banks stock returns and the performances of the banks in terms of economic value created with the upgrades or downgrades of Fitch Rating Long Term in the reference year. This

seems to highlight, in a first approximation, that the share prices of the banks investigated are not influenced by the reports of Fitch;

- a negative significant correlation emerges between the annual banks' capacity to create economic value and the annual volatility of their shares prices. It therefore seems that the increase of the level of the share price's risk inhibits the ability of the banks to create economic value. This is absolutely in keeping with that shown above, since an increase in the risk perceived by the market tends inevitably to increase the bank's $K_e$, raising the threshold profit in terms of economic value created;
- a positive significant correlation emerges instead between the banks stock returns and the annual volatility of their shares prices. It therefore seems that the banks share prices are positively influenced by the speculative risk of price, defined as the volatility of their stock returns around an average value. This seems to highlight a clear outlook towards the short-term by the operators in the formation of their investment decisions in the banks' shares[8].

### *5.2. Empirical results based on the neural network model*

This paragraph introduces the empirical results produced by the application of the 2 $ANN_m$ developed in accordance with the methodology outlined in paragraphs 3 and 4 (Table 4).
The analysis of the data reveals that the variables used as input of the 2 $ANN_m$ do not have a significant influence on the share prices of the banks (output of the $ANN_m$).
As a result, in fact, of the increase of 10% of each input, the per cent variations of the outputs of the 2 $ANN_m$ compared with the outputs expected are included among the maximum limit of 6,04% (as a result of the variation of the equity at time "t") and the minimum limit of -5,80% (as a result of the variation of the Price to Earning ratio at time "t")[9].
According to the $ANN_m$ developed, therefore, the inputs analyzed do not influence the share prices of the banks, both in the year of the inputs' accounting and in the following one. And I am not so surprised by this. As it is possible to deduce from the portfolio of the inputs analyzed (Table 4), the 2 $ANN_m$ have been developed using as inputs information – or data – characterized by a quantitative nature and freely accessible through the public disclosure of the banks or the financial markets. In other words, the 2 $ANN_m$ have been developed using as inputs indicators characterized by a not innovative nature – these being derived from information already incorporated in the share prices – as required by the economic theory assuming a good efficiency of the markets.
What then emerges represents a not surprising fact which supports the research hypothesis introduced and leads to evolve the artificial neural network model ($ANN_m$) developed in the direction that is illustrated in Appendix A.

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[8] About the outlook towards the short-term by the operators in the formation of their investment decisions in the listed company's shares, see Keynes (1936), book IV, chapter 12.
[9] It is excluded the case of the variation of the outputs of 9,72% at time "t" as a result of the variation of the Price to Book Value ratio, because the input and output are influenced by the same variation in the share price.

| Input of the 2 Artificial Neural Networks (time "t") | | | Output of the 1° Neural Network: Δ Market Price (time "t") Expected Output = - 0,6585 | | Output of the 2° Neural Network: Δ Market Price (time "t+1") Expected Output = - 0,4948 | |
|---|---|---|---|---|---|---|
| Input 1 | Net Income | $O = f[(1{,}10 * I_1); K\, I_{2\text{-}27}]$ | -0,6443 | ***2,16%*** | -0,4984 | ***-0,73%*** |
| Input 2 | Δ % Total Capital | $O = f[(1{,}10 * I_2); K\, I_{1\text{-}27}]$ | -0,6735 | ***-2,28%*** | -0,4994 | ***-0,93%*** |
| Input 3 | Δ % Equity | $O = f[(1{,}10 * I_3); K\, I_{1\text{-}27}]$ | -0,6187 | ***6,04%*** | -0,5080 | ***-2,67%*** |
| Input 4 | Δ % Total Capital Ratio | $O = f[(1{,}10 * I_4); K\, I_{1\text{-}27}]$ | -0,6587 | ***-0,03%*** | -0,4935 | ***0,26%*** |
| Input 5 | Δ % Tier 1 Capital Ratio | $O = f[(1{,}10 * I_5); K\, I_{1\text{-}27}]$ | d.n.c. | ***1,10%*** | d.n.c. | ***2,04%*** |
| Input 6 | Δ % Capital Funds/Liabilities | $O = f[(1{,}10 * I_6); K\, I_{1\text{-}27}]$ | -0,6495 | ***1,37%*** | -0,4926 | ***0,44%*** |
| Input 7 | Δ % Total Assets | $O = f[(1{,}10 * I_7); K\, I_{1\text{-}27}]$ | -0,6881 | ***-4,50%*** | -0,5008 | ***-1,21%*** |
| Input 8 | Δ % Total Earning Assets | $O = f[(1{,}10 * I_8); K\, I_{1\text{-}27}]$ | -0,6616 | ***-0,47%*** | -0,4885 | ***1,27%*** |
| Input 9 | Δ % Fixed Assets | $O = f[(1{,}10 * I_9); K\, I_{1\text{-}27}]$ | -0,6550 | ***0,53%*** | -0,4988 | ***-0,81%*** |
| Input 10 | Δ % Intangible Assets (by bank's accounting) | $O = f[(1{,}10 * I_{10}); K\, I_{1\text{-}27}]$ | -0,6331 | ***3,86%*** | -0,4805 | ***2,89%*** |
| Input 11 | Δ % Cost to Income Ratio | $O = f[(1{,}10 * I_{11}); K\, I_{1\text{-}27}]$ | -0,6544 | ***0,62%*** | -0,5016 | ***-1,37%*** |
| Input 12 | Δ % Net Interest Margin | $O = f[(1{,}10 * I_{12}); K\, I_{1\text{-}27}]$ | -0,6595 | ***-0,15%*** | -0,4955 | ***-0,14%*** |
| Input 13 | Knowledge Capital Earning | $O = f[(1{,}10 * I_{13}); K\, I_{1\text{-}27}]$ | -0,6605 | ***-0,30%*** | -0,4973 | ***-0,51%*** |
| Input 14 | Δ % Deposits & Short Term Funding | $O = f[(1{,}10 * I_{14}); K\, I_{1\text{-}27}]$ | -0,6582 | ***0,05%*** | -0,4859 | ***1,80%*** |
| Input 15 | Δ % Brand | $O = f[(1{,}10 * I_{15}); K\, I_{1\text{-}27}]$ | -0,6512 | ***1,11%*** | -0,4851 | ***1,96%*** |
| Input 16 | Δ % Dividend Pay Out Ratio | $O = f[(1{,}10 * I_{16}); K\, I_{1\text{-}27}]$ | d.n.c. | ***-1,96%*** | d.n.c. | ***-2,43%*** |
| Input 17 | Δ % Price to Book Value | $O = f[(1{,}10 * I_{17}); K\, I_{1\text{-}27}]$ | -0,5945 | ***9,72%*** | -0,4978 | ***-0,61%*** |
| Input 18 | Δ % Price to Earning | $O = f[(1{,}10 * I_{18}); K\, I_{1\text{-}27}]$ | -0,6967 | ***-5,80%*** | -0,4717 | ***4,67%*** |
| Input 19 | Δ % Reputational Capital Value | $O = f[(1{,}10 * I_{19}); K\, I_{1\text{-}27}]$ | -0,6615 | ***-0,46%*** | -0,4963 | ***-0,30%*** |
| Input 20 | Δ % Return on Average Equity | $O = f[(1{,}10 * I_{20}); K\, I_{1\text{-}27}]$ | -0,6608 | ***-0,35%*** | -0,4957 | ***-0,18%*** |
| Input 21 | Δ % Ke | $O = f[(1{,}10 * I_{21}); K\, I_{1\text{-}27}]$ | -0,6661 | ***-1,15%*** | -0,5010 | ***-1,25%*** |
| Input 22 | Δ % Economic Capital (Net Income/Ke) | $O = f[(1{,}10 * I_{22}); K\, I_{1\text{-}27}]$ | -0,6530 | ***0,84%*** | -0,4981 | ***-0,67%*** |
| Input 23 | Δ % Euribor | $O = f[(1{,}10 * I_{23}); K\, I_{1\text{-}27}]$ | d.n.c. | ***0,31%*** | d.n.c. | ***1,05%*** |
| Input 24 | Δ % Beta | $O = f[(1{,}10 * I_{24}); K\, I_{1\text{-}27}]$ | -0,6462 | ***1,87%*** | -0,5079 | ***-2,65%*** |
| Input 25 | Volatility of stock price | $O = f[(1{,}10 * I_{25}); K\, I_{1\text{-}27}]$ | -0,6643 | ***-0,88%*** | -0,5088 | ***-2,83%*** |
| Input 26 | Δ % Net Income | $O = f[(1{,}10 * I_{26}); K\, I_{1\text{-}27}]$ | -0,6578 | ***0,11%*** | -0,4958 | ***-0,20%*** |
| Input 27 | Δ Fitch Rating Long Term | $O = f[(1{,}10 * I_{27}); K\, I_{1\text{-}26}]$ | -0,6481 | ***1,58%*** | -0,4919 | ***0,59%*** |

**Table 4: Empirical results based on the artificial neural network model**

## 6. Concluding remarks

The empirical results emerging through the application to the panel of the banks analyzed of the linear and non-linear methods of analysis described in the paper seem to support the research hypothesis introduced in paragraph 1.

In particular the analysis of the data reveals the following relevant aspects:

1. the variables characterized by a purely quantitative nature and measurable using public and not innovative information do not seem to express a significant influence

on the share prices of the banks. This is because these variables are already reflected and incorporated in the share prices, assuming a good efficiency of the markets;

2. in the processes of creation and diffusion of economic value of a bank, the risk of the bank's management – in its different configurations – has a fundamental importance which is however difficult to quantify essentially because the risk management represents a process characterized by an intangible nature, being directly traceable back to the bank's patrimony of skills, information, knowledge, reputation and organization.

The two considerations highlighted above lead indirectly to a third consideration:

3. there are some banks' variables – often characterized by an invisible and intangible nature – which contribute to the creation of the value and the price of the economic capital of a bank but are difficult to measure or account through linear methods of analysis that consider only quantitative and public data. So it would be superficial not analyze these intangibles variables because the empirical evidence shows that these intangibles have a fundamental importance both in determining the expectations of investors in the banking shares and in determining the competitive advantage of the bank in the market.

The three considerations highlighted above lead to a fourth consideration which is essentially methodological and is about the effectiveness of an integrated approach, which is based on the joint use of linear and non-linear methods of analysis to study the phenomena analyzed in this paper. Through this research, in fact, it emerges that the comparison of linear regression methods and artificial neural network models is able to discover aspects of the phenomena analyzed otherwise invisible.

As highlighted previously, in fact, the artificial neural networks are non-linear mathematical models particularly suited to analyze and interpret – revealing hidden relationships that govern the data – complex and often obscure phenomena and processes, which are, for example, those governing the dynamics of the share prices in financial markets[10]. The artificial neural networks are in fact "intelligent" logical-mathematical models, which are able to incorporate and to generate the knowledge about the logic of the shares' demand and supply through learning.

In order to be efficient, an artificial neural network must be properly developed and trained. About the adequacy of the $ANN_m$'s training, there are two weaknesses of the $ANN_m$ developed in this research that are about the number of the records (patterns of inputs and output) used to train the $ANN_m$ and the purely quantitative and public nature of the inputs analyzed.

As highlighted previously the artificial neural networks have as many chances to be efficient as more numerous are the series of data (records) used to train the $ANN_m$. In this research the number of the records (patterns of inputs and output) used to train the $ANN_m$ was relatively small. The records used are 48 because they were in fact calculated for the 16 banks investigated and for the 3 years analyzed (48 patterns of input and output or 48 records).

[10] As highlighted previously, in fact, the artificial neural networks have the ability to create – through learning from historical data – models which are able to reproduce the phenomenon analyzed minimising the inference request to the planner of the mathematical model whose rationality often can not extract – at least quickly – the hidden relationships that bind the variables analyzed or the algorithms that govern the phenomena analyzed.

The second weakness of the $ANN_m$ developed is about the purely quantitative and public nature of the inputs analyzed. In order to develop an efficient $ANN_m$, in fact, it would be necessary to consider and analyse all the phenomena which are able to influence – both directly and indirectly – the share prices of the banks.
However if the first weakness can be easily remedied by increasing the number of the banks analyzed and extending the period of analysis in order to increase the number of the records, there would be further difficulties – from the viewpoint of a researcher outside the bank – where you would overcome the second weakness. Many phenomena that can significantly influence the share prices of the banks have, in fact, essentially a qualitative nature and a profile of confidentiality which hinders their disclosure. Many of these phenomena, therefore, are hardly measurable and, consequently, analyzable because of their qualitative nature. And where quantifiable, the information on these phenomena have a profile of confidentiality which hinders their disclosure.
These arguments, however, are not reasons enough to hinder the theoretical evolution of the $ANN_m$ developed (see Appendix A). Obviously the artificial neural networks, which aim to predict bank stock returns through a comprehensive study of the possible relevant phenomena, will have inevitably a disclosure and, therefore, an utility strictly within the bank, as means of strategic planning and internal control of management. This is because only the management of the bank has all those confidential and qualitative information that should be used as input of an artificial neural network which has such an ambitious aim.

## Appendix A

In this Appendix it is proposed an evolution of the $ANN_m$ described in paragraph 3, with similar mathematical architecture but different input (see Table 5 and Figure 2)[11].

| - | **Indicators about the variation of the 3 different forms of capital of a bank in the period between $t_0$ e $t_1$** <br> **Input of the Artificial Neural Network** |
|---|---|
| | **I. Indicators about the variation of the financial capital and the financial capital adequacy to risk weighted assets** |
| | ***I a). Indicator about the variation of the equity*** |
| *Input 1* | Net Income |
| | ***I b). Indicator about the variation of the tier 1 and total capital*** |
| *Input 2* | Δ Total Capital |
| *Input 3* | Δ Tier 1 Capital |
| | ***I c). Indicators about the variation of the financial capital adequacy to risk weighted assets*** |
| *Input 4* | Δ Total Capital Ratio |
| *Input 5* | Δ Tier 1 Capital Ratio |
| | **II. Indicators about the variation of the tangible and visible capital** |
| *Input 6* | Δ Tangible assets |
| *Input 7* | Δ Structure physical network of production and distribution (branches, agencies, employees, etc.) |
| | **III. Indicators about the variation of the intangible and invisible capital** |
| | ***III a). Indicators about the variation of the organizational capital*** |
| | *Indicators of investments* |
| *Input 8* | Δ Investments incurred for research and development of organizational, productive or distributive solutions |
| *Input 9* | Δ Investments incurred for research and development of models for risk management and capital allocation |
| *Input 10* | Δ Investments incurred for the training of employees |
| *Input 11* | Δ Investments incurred for periodic evaluation of employees |
| *Input 12* | Δ Investments incurred for finding information on their customers |
| *Input 13* | Δ Investments incurred for the implementation and development of systems of CRM |
| *Input 14* | Δ Investments incurred for ICT and technological innovation |
| *Input 15* | Δ Investments incurred for systems of accounting and reporting on their intangible assets |
| *Input 16* | Δ Investments incurred for systems of protection and control of their intangible assets |
| | *Indicators of results* |
| *Input 17* | Δ Efficiency and general optimization of business processes |
| *Input 18* | Δ Completeness of the portfolio of products and services |
| *Input 19* | Δ Optimization, capillarity and efficiency of the distribution network (territorial organisation) |
| *Input 20* | Δ Differentiation of the strategy compared to competitors |
| *Input 21* | Δ Efficiency in the credit risk management |
| *Input 22* | Δ Efficiency in the market risk management |
| *Input 23* | Δ Efficiency in the operational risk management |

[11] In the description of the input of the $ANN_m$, then, it is omitted the analysis of the mathematical architecture, for which you refer to in paragraph 3.

| | |
|---|---|
| *Input 24* | Δ Completeness and efficiency in the process of risk management and capital allocation |
| *Input 25* | Δ Skills of the employees |
| *Input 26* | Δ Information about the customers |
| *Input 27* | Δ Leadership in innovation |
| *Input 28* | Δ Number of PC to employees |
| *Input 29* | Δ Annual average of transactions made through the telematic channel |
| *Input 30* | Δ Efficiency of services offered by the Intranet |
| *Input 31* | Δ Efficiency of organisational systems aimed to share information within the company |
| *Input 32* | Δ Efficiency of organisational systems aimed to share information with the customers |
| *Input 33* | Δ Degree of interconnection and integration between the company and its stakeholders |
| *Input 34* | Δ Efficiency and effectiveness of systems for accounting and reporting on their intangible assets |
| *Input 35* | Δ Ability to exclude competitors from the enjoyment of the benefits arising from investment in intangibles |
| *Input 36* | Δ Ability to manage the intangible assets |
| | |
| | ***III b). Indicators about the variation of the reputational (ralational) capital*** |
| | *III b 1). Indicators about the variation of the reputation towards customers* |
| | *Indicators of investments* |
| *Input 37* | Δ Investments incurred to acquire and maintain the customers |
| *Input 38* | Δ Investments incurred to improve the service to customers |
| | |
| | *Indicators of results* |
| *Input 39* | Δ Funding |
| *Input 40* | Δ Positioning in the hierarchy of leadership in the funding |
| *Input 41* | Δ Fees earned on investment services |
| *Input 42* | Δ Market shares (for products, for territorial areas and customer segments) |
| *Input 43* | Δ Cross-selling |
| *Input 44* | Δ Coefficient of attracting customers (segments) |
| *Input 45* | Δ Average length of the customer relationship (segments) |
| *Input 46* | Δ Customer Retention Rate |
| *Input 47* | Δ Customer Loyalty |
| *Input 48* | Δ Number of complaints received |
| *Input 49* | Δ Accessibility (simplicity and speed of access) by customers to products and services offered |
| *Input 50* | Δ The average time of waiting customers in the branches |
| *Input 51* | Δ Elasticity average price of the customers |
| *Input 52* | Δ Customer Equity |
| | |
| | *III b 2). Indicators about the variation of the reputation towards financial markets* |
| | *Indicators of investments* |
| *Input 53* | Δ Disclosure towards financial markets |
| *Input 54* | Δ Performances about shareholder value added |
| *Input 55* | Δ Financial and patrimonial strength |
| | *Indicators of investments (towards shareholders)* |
| *Input 56* | Δ Dividend pay out ratio |
| *Input 57* | Δ Transparency of corporate governance |
| *Input 58* | Δ Disclosure about economic, financial and patrimonial strength of the bank |
| | *Indicators of investments (towards creditors-bondholders)* |
| *Input 59* | Δ Punctuality in the service of credit |
| | |
| | *Indicators of results* |
| *Input 60* | Δ Rating |

| | |
|---|---|
| *Input 61* | Δ Market consensus |
| *Input 62* | Δ Attention of financial analysts |
| *Input 63* | Δ Price to Book Value ratio |
| *Input 64* | Δ $K_e$ |
| *Input 65* | Δ Guarantees |
| *Input 66* | Δ $K_d$ |
| | *III b 3). Indicators about the variation of the reputation towards employees* |
| | *Indicators of investments* |
| *Input 67* | Δ Payment policy of employees |
| *Input 68* | Δ Working conditions for employees |
| *Input 69* | Δ Merit and fairness in the evaluation of career development within the bank |
| *Input 70* | Δ Merit and fairness in the recruitment |
| | *Indicators of results* |
| *Input 71* | Δ Turn around of the management suffered by the bank |
| *Input 72* | Δ Requests for work and c.v. received |
| *Input 73* | Δ Justification and a sense of belonging to the bank by employees |
| | *III b 4). Indicators about the variation of the reputation towards suppliers* |
| | *Indicators of investments* |
| *Input 74* | Δ Punctuality in the service of credit |
| *Input 75* | Δ Working conditions and payment policy |
| *Input 76* | Δ Merit and fairness in the assignment of the supply tasks |
| | *Indicators of results* |
| *Input 77* | Δ Turn around of the suppliers suffered by the bank |
| *Input 78* | Δ Quality, professionalism and punctuality of the supply service |

| | **Output of the Artificial Neural Network** |
|---|---|
| *Output 1* | ***Δ % Value of the Bank's Economic Capital between $t_0$ e $t_1$*** |
| *Output 2* | ***Δ % Price of the Bank's Economic Capital between $t_0$ e $t_1$*** |

**Table 5: New Input for the Artificial Neural Network Model**

The objective of this $ANN_m$ is to analyse the impact of each input analyzed to the economic value and to the market value of the bank (2 outputs of this $ANN_m$).
From the analysis of the portfolio of the inputs considered (inputs representative of phenomena within the bank)[12], it is known as many of these inputs have a purely qualitative nature and therefore it is difficult to quantify their value. In order to estimate the variation – between $t_0$ and $t_1$ – of each input considered, the management of the bank can express evaluations on a scale from “-10” to “+10”.
A value of “-10” indicates a maximum negative variation.
A value of “+10” indicates a maximum positive variation.
A value of “0” indicates no variation in the period considered.

[12] In this $ANN_m$ external phenomena of the bank are not considered.

The period between $t_0$ and $t_1$ may be 3 years in order to consent to the investments in intangibles to produce their effects on the value and the price of the economic capital of a bank.

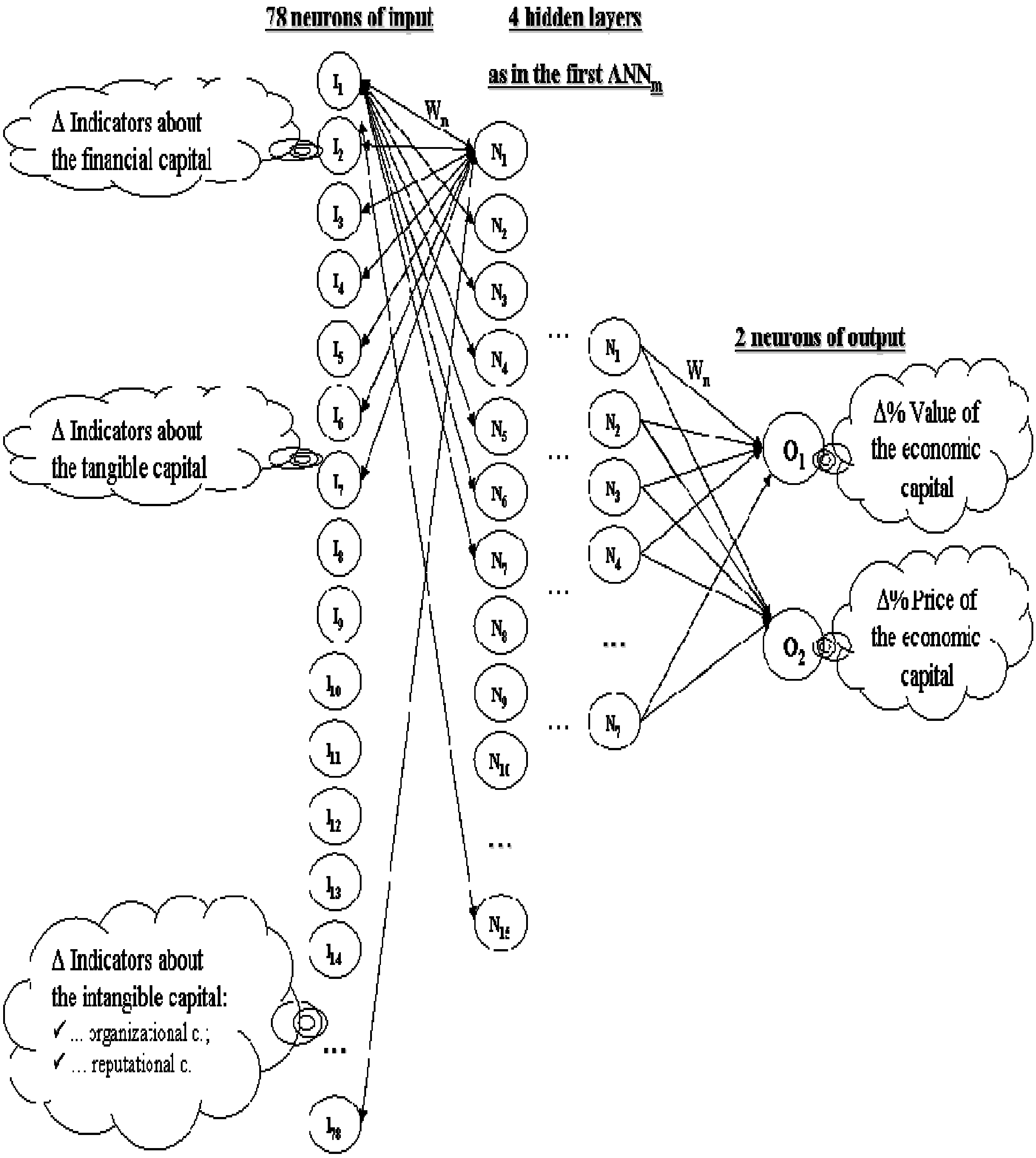


**Figure 2: Architecture of the evolution of the $ANN_m$ described in paragraph 3**

# Appendix B

| Banks | Beta | P/BV | P/Earning | ROAE | D | $K_e$ | ROAE - Ke |
|---|---|---|---|---|---|---|---|
| **ABN Amro** | 1,30 | 1,54 | 10,26 | 14,26 | 58,63 | 10,92 | 3,34 |
| **Banca Carige** | 0,07 | 1,36 | 26,68 | 5,19 | 111,24 | 3,71 | 1,48 |
| **Banca CR Firenze** | 0,27 | 1,16 | 13,14 | 9,05 | 58,43 | 4,88 | 4,17 |
| **Banca Lombarda e Piemontese** | 0,21 | 1,27 | 17,08 | 7,98 | 61,95 | 4,53 | 3,45 |
| **Banca Monte dei Paschi di Siena** | 0,84 | 0,90 | 9,94 | 8,83 | 37,14 | 8,22 | 0,61 |
| **Banco Bilbao Vizcaya Argentaria** | 1,15 | 1,58 | 11,82 | 12,80 | 56,27 | 10,04 | 2,76 |
| **Banco Santander Central Hispano** | 1,15 | 1,31 | 11,20 | 11,00 | 63,77 | 10,04 | 0,96 |
| **BNP Paribas** | 1,14 | 1,09 | 9,56 | 11,99 | 29,57 | 9,98 | 2,01 |
| **Capitalia** | 1,15 | 0,38 | -4,93 | -8,04 | 0,00 | 10,04 | -18,08 |
| **Commerzbank** | 0,90 | 0,40 | -15,01 | -2,31 | -20,07 | 8,57 | -10,88 |
| **Credito Emiliano** | 1,02 | 1,62 | 12,75 | 13,05 | 48,62 | 9,28 | 3,77 |
| **Deutsche Bank** | 1,07 | 0,97 | 68,73 | 1,27 | 190,43 | 9,57 | -8,30 |
| **Intesa Sanpaolo** | 1,25 | 0,88 | 43,08 | 1,93 | 39,13 | 10,63 | -8,70 |
| **Mediobanca** | 0,81 | 1,25 | 23,29 | 5,56 | 44,56 | 8,05 | -2,49 |
| **Société Générale** | 1,22 | 1,28 | 15,99 | 7,92 | 60,52 | 10,45 | -2,53 |
| **UniCredito Italiano** | 0,98 | 1,77 | 12,09 | 14,82 | 50,47 | 9,04 | 5,78 |
| ***Average of Italian Banks*** | ***0,73*** | ***1,18*** | ***17,01*** | ***6,49*** | ***50,17*** | ***7,60*** | ***-1,11*** |
| ***Average of Foreign Banks*** | ***1,13*** | ***1,17*** | ***16,08*** | ***8,13*** | ***62,73*** | ***9,94*** | ***-1,81*** |
| ***Average of Banks*** | ***0,91*** | ***1,17*** | ***16,61*** | ***7,21*** | ***55,67*** | ***8,62*** | ***-1,42*** |

**Table 6: Shareholder Value Added in Banks in 2002**

| Banks | Beta | P/BV | P/Earning | ROAE | D | $K_e$ | ROAE - Ke |
|---|---|---|---|---|---|---|---|
| **ABN Amro** | 1,21 | 1,70 | 8,92 | 20,06 | 45,21 | 10,60 | 9,46 |
| **Banca Carige** | 0,10 | 1,58 | 30,09 | 5,66 | 102,45 | 2,99 | 2,67 |
| **Banca CR Firenze** | 0,14 | 1,37 | 15,83 | 8,81 | 86,78 | 3,26 | 5,55 |
| **Banca Lombarda e Piemontese** | 0,33 | 1,26 | 21,40 | 6,19 | 64,28 | 4,56 | 1,63 |
| **Banca Monte dei Paschi di Siena** | 1,19 | 1,07 | 50,33 | 2,22 | 112,16 | 10,46 | -8,24 |
| **Banco Bilbao Vizcaya Argentaria** | 1,19 | 1,91 | 12,08 | 15,75 | 46,30 | 10,46 | 5,29 |
| **Banco Santander Central Hispano** | 1,22 | 1,86 | 13,85 | 13,50 | 54,42 | 10,67 | 2,83 |
| **BNP Paribas** | 1,19 | 1,32 | 11,39 | 11,98 | 33,10 | 10,46 | 1,52 |
| **Capitalia** | 1,14 | 0,73 | 108,94 | 0,66 | 93,62 | 10,12 | -9,46 |
| **Commerzbank** | 1,31 | 0,92 | -4,17 | -22,13 | 0,00 | 11,29 | -33,42 |
| **Credito Emiliano** | 0,99 | 1,71 | 15,43 | 11,25 | 54,09 | 9,09 | 2,16 |
| **Deutsche Bank** | 1,05 | 1,51 | 28,01 | 5,10 | 60,44 | 9,50 | -4,40 |
| **Intesa Sanpaolo** | 1,50 | 1,14 | 14,76 | 8,50 | 25,82 | 12,59 | -4,09 |
| **Mediobanca** | 1,04 | 1,35 | 107,30 | 1,27 | 3,85 | 9,43 | -8,16 |
| **Société Générale** | 1,13 | 1,52 | 10,72 | 14,75 | 38,34 | 10,05 | 4,70 |
| **UniCredito Italiano** | 0,82 | 1,93 | 12,92 | 15,21 | 51,81 | 7,93 | 7,28 |
| ***Average of Italian Banks*** | ***0,81*** | ***1,35*** | ***41,89*** | ***6,64*** | ***66,10*** | ***7,83*** | ***-1,19*** |
| ***Average of Foreign Banks*** | ***1,19*** | ***1,54*** | ***11,54*** | ***8,43*** | ***39,69*** | ***10,43*** | ***-2,00*** |
| ***Average of Banks*** | ***0,97*** | ***1,43*** | ***28,61*** | ***7,42*** | ***54,54*** | ***8,97*** | ***-1,54*** |

**Table 7: Shareholder Value Added in Banks in 2003**

| Banks | Beta | P/BV | P/Earning | ROAE | D | $K_e$ | ROAE - Ke |
|---|---|---|---|---|---|---|---|
| **ABN Amro** | 0,90 | 1,63 | 7,58 | 25,06 | 42,26 | 8,46 | 16,61 |
| **Banca Carige** | 0,13 | 1,66 | 27,29 | 6,61 | 80,31 | 3,03 | 3,58 |
| **Banca CR Firenze** | 0,50 | 1,00 | 12,41 | 9,90 | 50,33 | 5,64 | 4,27 |
| **Banca Lombarda e Piemontese** | 0,35 | 1,20 | 17,03 | 7,17 | 61,17 | 4,58 | 2,59 |
| **Banca Monte dei Paschi di Siena** | 1,04 | 0,88 | 10,49 | 8,41 | 50,00 | 9,44 | -1,03 |
| **Banco Bilbao Vizcaya Argentaria** | 1,17 | 2,17 | 13,86 | 20,29 | 46,95 | 10,36 | 9,93 |
| **Banco Santander Central Hispano** | 1,02 | 1,37 | 14,35 | 11,28 | 55,72 | 9,30 | 1,98 |
| **BNP Paribas** | 1,06 | 1,32 | 9,46 | 14,28 | n.d | 9,58 | 4,70 |
| **Capitalia** | 1,61 | 0,95 | 12,32 | 8,49 | 30,16 | 13,46 | -4,97 |
| **Commerzbank** | 1,10 | 0,96 | 20,48 | 4,54 | 33,86 | 9,87 | -5,33 |
| **Credito Emiliano** | 0,80 | 1,79 | 13,16 | 14,58 | 49,57 | 7,75 | 6,83 |
| **Deutsche Bank** | 1,13 | 1,57 | 14,37 | 10,32 | 37,42 | 10,08 | 0,24 |
| **Intesa Sanpaolo** | 1,24 | 1,21 | 10,79 | 12,15 | 38,47 | 10,85 | 1,30 |
| **Mediobanca** | 0,91 | 1,73 | 16,82 | 10,72 | 42,74 | 8,53 | 2,19 |
| **Société Générale** | 1,15 | 1,54 | 9,63 | 16,48 | 59,08 | 10,22 | 6,26 |
| **UniCredito Italiano** | 0,77 | 1,85 | 11,93 | 15,29 | n.d | 7,54 | 7,75 |
| ***Average of Italian Banks*** | ***0,82*** | ***1,36*** | ***14,69*** | ***10,37*** | ***50,34*** | ***7,87*** | ***2,50*** |
| ***Average of Foreign Banks*** | ***1,08*** | ***1,51*** | ***12,82*** | ***14,61*** | ***45,88*** | ***9,69*** | ***4,91*** |
| ***Average of Banks*** | ***0,93*** | ***1,43*** | ***13,87*** | ***12,22*** | ***48,43*** | ***8,67*** | ***3,56*** |

**Table 8: Shareholder Value Added in Banks in 2004**

| Banks | Beta | P/BV | P/Earning | ROAE | D | $K_e$ | ROAE - Ke |
|---|---|---|---|---|---|---|---|
| **ABN Amro** | 0,87 | 1,84 | 9,49 | 22,98 | n.d | 8,26 | 14,72 |
| **Banca Carige** | 0,29 | 1,80 | 23,45 | 7,78 | 65,14 | 4,23 | 3,55 |
| **Banca CR Firenze** | 0,59 | 2,07 | 16,25 | 10,24 | 33,73 | 6,31 | 3,93 |
| **Banca Lombarda e Piemontese** | 0,52 | 1,63 | 13,65 | 12,32 | 45,34 | 5,83 | 6,49 |
| **Banca Monte dei Paschi di Siena** | 0,75 | 1,43 | 11,88 | 11,60 | 50,62 | 7,43 | 4,18 |
| **Banco Bilbao Vizcaya Argentaria** | 0,90 | 2,76 | 12,56 | 24,05 | 28,66 | 8,47 | 15,58 |
| **Banco Santander Central Hispano** | 1,06 | 1,43 | 10,33 | 14,89 | 25,84 | 9,58 | 5,31 |
| **BNP Paribas** | 1,13 | 1,40 | 9,11 | 16,93 | n.d | 10,06 | 6,87 |
| **Capitalia** | 0,88 | 1,32 | 10,52 | 12,82 | n.d | 8,33 | 4,49 |
| **Commerzbank** | 1,16 | 1,47 | 13,45 | 12,06 | 25,81 | 10,27 | 1,79 |
| **Credito Emiliano** | 0,59 | 2,03 | 9,77 | 22,23 | 58,98 | 6,31 | 15,92 |
| **Deutsche Bank** | 1,28 | 1,76 | 12,62 | 14,73 | 36,44 | 11,10 | 3,63 |
| **Intesa Sanpaolo** | 0,91 | 1,43 | 8,55 | 18,06 | n.d | 8,54 | 9,52 |
| **Mediobanca** | 0,90 | 2,20 | 17,79 | 12,35 | 0,91 | 8,47 | 3,88 |
| **Société Générale** | 1,16 | 1,73 | 9,15 | 20,90 | 36,55 | 10,27 | 10,63 |
| **UniCredito Italiano** | 0,81 | 1,62 | 22,09 | 7,32 | n.d | 7,84 | -0,52 |
| ***Average of Italian Banks*** | ***0,69*** | ***1,72*** | ***14,88*** | ***12,75*** | ***42,45*** | ***7,03*** | ***5,71*** |
| ***Average of Foreign Banks*** | ***1,08*** | ***1,77*** | ***10,96*** | ***18,08*** | ***30,66*** | ***9,72*** | ***8,36*** |
| ***Average of Banks*** | ***0,86*** | ***1,74*** | ***13,17*** | ***15,08*** | ***37,09*** | ***8,21*** | ***6,87*** |

**Table 9: Shareholder Value Added in Banks in 2005**

| Banks | Δ % Euribor | Δ % $K_e$ | Δ % Total Capital | Δ % Total Capital Ratio | Δ % Net Income | Δ Rating | Volatility % Market Price | ROAE - $K_e$ % | Δ % Market Price |
|---|---|---|---|---|---|---|---|---|---|
| **ABN Amro** | -30,30% | -2,91% | -0,90% | 1,74% | 41,41% | -2 | 38,81% | 9,46 | 19,06% |
| **Banca Carige** | -30,30% | -19,52% | 43,42% | 30,00% | 20,71% | 0 | 31,25% | 2,67 | 38,73% |
| **Banca CR Firenze** | -30,30% | -33,22% | 0,00% | 0,00% | 0,93% | 0 | 28,23% | 5,55 | 21,57% |
| **Banca Lombarda e Piemontese** | -30,30% | 0,73% | 12,66% | 2,00% | -11,95% | 0 | 17,14% | 1,63 | 9,98% |
| **Banca Monte dei Paschi di Siena** | -30,30% | 27,25% | 13,25% | 12,50% | -74,36% | 0 | 35,86% | -8,24 | 12,05% |
| **Banco Bilbao Vizcaya Argentaria** | -30,30% | 4,23% | 2,74% | -3,57% | 17,47% | 0 | 39,27% | 5,29 | 20,07% |
| **Banco Santander Central Hispano** | -30,30% | 6,28% | 8,32% | -0,93% | 16,03% | 0 | 48,99% | 2,83 | 43,58% |
| **BNP Paribas** | -30,30% | 4,84% | 6,70% | 18,35% | 8,86% | 0 | 36,14% | 1,52 | 28,55% |
| **Capitalia** | -30,30% | 0,81% | -4,69% | 4,08% | 108,62% | 0 | 88,36% | -9,46 | 90,16% |
| **Commerzbank** | -30,30% | 31,64% | -7,18% | 5,69% | -728,62% | 0 | 77,17% | -33,42 | 108,72% |
| **Credito Emiliano** | -30,30% | -2,00% | 23,06% | 7,14% | -9,62% | 0 | 45,53% | 2,16 | 8,97% |
| **Deutsche Bank** | -30,30% | -0,70% | 0,03% | 10,32% | 243,83% | -1 | 52,51% | -4,40 | 49,66% |
| **Intesa Sanpaolo** | -30,30% | 18,49% | -1,96% | 5,41% | 363,04% | 0 | 47,30% | -4,09 | 58,29% |
| **Mediobanca** | -30,30% | 17,25% | -10,68% | -18,14% | -76,19% | 0 | 27,91% | -8,16 | 9,69% |
| **Société Générale** | -30,30% | -3,80% | 8,35% | 5,41% | 91,62% | -1 | 38,10% | 4,70 | 26,13% |
| **UniCredito Italiano** | -30,30% | -12,36% | 0,52% | -6,72% | 5,79% | 0 | 33,88% | 7,28 | 12,34% |
| ***Average of Italian Banks*** | | ***-0,28%*** | ***8,40%*** | ***4,03%*** | ***36,33%*** | | ***39,49%*** | ***-1,19*** | ***29,09%*** |
| ***Average of Foreign Banks*** | | ***5,65%*** | ***2,58%*** | ***5,29%*** | ***-44,20%*** | | ***47,29%*** | ***-2,00*** | ***42,25%*** |
| ***Average of Banks*** | | ***2,31%*** | ***5,85%*** | ***4,58%*** | ***1,10%*** | | ***42,90%*** | ***-1,54*** | ***34,85%*** |

**Table 10: Risk and Value in 2003**

| Banks | Δ % Euribor | Δ % $K_e$ | Δ % Total Capital | Δ % Total Capital Ratio | Δ % Net Income | Δ Rating | Volatility % Market Price | ROAE - $K_e$ % | Δ % Market Price |
|---|---|---|---|---|---|---|---|---|---|
| **ABN Amro** | -8,26% | -20,24% | -0,78% | -3,42% | 28,26% | 0 | 25,14% | 16,61 | 5,07% |
| **Banca Carige** | -8,26% | 1,36% | -4,85% | -16,24% | 27,57% | 0 | 23,53% | 3,58 | 6,25% |
| **Banca CR Firenze** | -8,26% | 72,83% | 29,84% | 1,02% | 68,75% | 0 | 35,03% | 4,27 | 26,61% |
| **Banca Lombarda e Piemontese** | -8,26% | 0,30% | 9,01% | -0,98% | 23,97% | 0 | 13,36% | 2,59 | -1,92% |
| **Banca Monte dei Paschi di Siena** | -8,26% | -9,76% | 4,42% | 1,01% | 306,98% | 0 | 17,11% | -1,03 | 4,78% |
| **Banco Bilbao Vizcaya Argentaria** | -8,26% | -1,00% | 7,11% | 15,74% | 10,21% | 0 | 23,37% | 9,93 | 19,18% |
| **Banco Santander Central Hispano** | -8,26% | -12,82% | 91,04% | 22,64% | 23,64% | 0 | 19,72% | 1,98 | -2,77% |
| **BNP Paribas** | -8,26% | -8,41% | 4,87% | -17,83% | 26,00% | 0 | 14,37% | 4,70 | 6,78% |
| **Capitalia** | -8,26% | 33,00% | 2,31% | 4,90% | 1186,81% | 0 | 45,99% | -4,97 | 45,26% |
| **Commerzbank** | -8,26% | -12,60% | -3,44% | -3,08% | 119,87% | 0 | 23,09% | -5,33 | -2,51% |
| **Credito Emiliano** | -8,26% | -14,75% | 20,67% | 17,78% | 50,74% | 0 | 20,52% | 6,83 | 28,02% |
| **Deutsche Bank** | -8,26% | 6,03% | -4,21% | -5,04% | 81,10% | 0 | 39,04% | 0,24 | -0,58% |
| **Intesa Sanpaolo** | -8,26% | -13,80% | 2,50% | -0,85% | 51,80% | 0 | 28,25% | 1,30 | 19,59% |
| **Mediobanca** | -8,26% | -9,63% | 6,96% | 3,61% | 787,50% | 0 | 30,23% | 2,19 | 38,49% |
| **Société Générale** | -8,26% | 1,65% | 6,85% | 1,71% | 20,22% | 0 | 14,19% | 6,26 | 6,36% |
| **UniCredito Italiano** | -8,26% | -4,88% | 11,20% | 4,50% | 7,36% | 0 | 15,37% | 7,75 | -1,17% |
| ***Average of Italian Banks*** | | ***6,07%*** | ***9,12%*** | ***1,64%*** | ***279,05%*** | | ***25,49%*** | ***2,50*** | ***18,44%*** |
| ***Average of Foreign Banks*** | | ***-6,77%*** | ***14,49%*** | ***1,53%*** | ***44,19%*** | | ***22,70%*** | ***4,91*** | ***4,50%*** |
| ***Average of Banks*** | | ***0,45%*** | ***11,47%*** | ***1,59%*** | ***176,30%*** | | ***24,27%*** | ***3,56*** | ***12,34%*** |

**Table 11: Risk and Value in 2004**

| Banks | Δ % Euribor | Δ % $K_e$ | Δ % Total Capital | Δ % Total Capital Ratio | Δ % Net Income | Δ Rating | Volatility % Market Price | ROAE - $K_e$ % | Δ % Market Price |
|---|---|---|---|---|---|---|---|---|---|
| **ABN Amro** | 5,21% | -2,33% | 30,04% | 15,93% | 1,44% | 0 | 19,47% | 14,72 | 13,34% |
| **Banca Carige** | 5,21% | 39,85% | 1,96% | -15,31% | 29,78% | 0 | 14,08% | 3,55 | 11,37% |
| **Banca CR Firenze** | 5,21% | 12,06% | -6,94% | -13,13% | 6,19% | 0 | 36,70% | 3,93 | 38,85% |
| **Banca Lombarda e Piemontese** | 5,21% | 27,34% | -2,16% | -3,96% | 54,85% | 0 | 20,96% | 6,49 | 22,61% |
| **Banca Monte dei Paschi di Siena** | 5,21% | -21,36% | -2,37% | -8,00% | 32,85% | 0 | 44,30% | 4,18 | 50,19% |
| **Banco Bilbao Vizcaya Argentaria** | 5,21% | -18,27% | 0,00% | -4,00% | 27,51% | 0 | 21,55% | 15,58 | 15,56% |
| **Banco Santander Central Hispano** | 5,21% | 2,96% | 20,44% | -0,77% | 68,91% | 0 | 18,83% | 5,31 | 22,12% |
| **BNP Paribas** | 5,21% | 5,00% | 14,33% | 3,77% | 26,05% | 0 | 29,42% | 6,87 | 28,23% |
| **Capitalia** | 5,21% | -38,14% | -10,18% | -10,28% | 70,95% | 1 | 35,79% | 4,49 | 45,10% |
| **Commerzbank** | 5,21% | 4,11% | 6,21% | -0,79% | 186,91% | 0 | 46,12% | 1,79 | 71,64% |
| **Credito Emiliano** | 5,21% | -18,52% | 0,34% | -6,60% | 75,75% | 0 | 26,51% | 15,92 | 29,00% |
| **Deutsche Bank** | 5,21% | 10,19% | 18,43% | 2,27% | 42,76% | 0 | 31,14% | 3,63 | 25,38% |
| **Intesa Sanpaolo** | 5,21% | -21,35% | -7,54% | -11,21% | 61,44% | 0 | 24,61% | 9,52 | 26,27% |
| **Mediobanca** | 5,21% | -0,70% | 6,50% | -2,49% | 30,43% | 0 | 32,24% | 3,88 | 35,43% |
| **Société Générale** | 5,21% | 0,52% | 33,65% | -5,04% | 43,29% | 0 | 31,48% | 10,63 | 39,57% |
| **UniCredito Italiano** | 5,21% | 4,02% | 144,53% | -11,21% | 22,00% | -1 | 31,79% | -0,52 | 37,59% |
| *Average of Italian Banks* | | ***-1,87%*** | ***13,79%*** | ***-9,13%*** | ***42,69%*** | | ***29,66%*** | ***5,71*** | ***32,94%*** |
| *Average of Foreign Banks* | | ***0,31%*** | ***17,59%*** | ***1,62%*** | ***56,69%*** | | ***28,29%*** | ***8,36*** | ***30,83%*** |
| *Average of Banks* | | ***-0,91%*** | ***15,45%*** | ***-4,43%*** | ***48,82%*** | | ***29,06%*** | ***6,87*** | ***32,02%*** |

**Table 12: Risk and Value in 2005**

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